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THE USE OF ARTIFICIAL INTELLIGENCE ON COMMODITY MARKETS

VYUŽITÍ UMĚLÉ INTELIGENCE NA KOMODITNÍCH TRZÍCH

DIPLOMOVÁ PRÁCE
MASTER'S THESIS

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DOSTÁL, P. Pokročilé metody rozhodování v podnikatelství a veřejné správě. Brno: CERM Akademické nakladatelství, 2012. 718 p. ISBN 978-80-7204-798-7, e-ISBN 978-80-7204-799-4.

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Abstrakt

Tato diplomová práce se zabývá problematikou obchodování na komoditních trzích. Řešení problematiky spočívá ve využití umělé inteligence, konkrétně neuronových sítí, k technické analýze vývoje ceny vybrané komodity a snaze o co nejpřesnější predikci budoucího vývoje ceny pro podporu investičního rozhodování. Model neuronové sítě je vytvořen a použit pro predikci v programu MATLAB.

Abstract

This master thesis focuses on the problem of trading on commodity markets. The solution of the problem is designed using the artificial intelligence, specifically neural networks, to determine the trend of a selected commodity price and predict the price movement in the future to support investment decision. The model of the neural network is created and used for prediction in the MATLAB program.

Klíčová slova

Unělé neuronové sítě, umělá inteligence, komoditní trhy, komodity, obchodování, predikce, předpověď, MATLAB.

Keywords

Artificial Neural Networks, ANN, artificial intelligence, commodity market, commodities, trading, prediction, MATLAB, futures.

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Čestné prohlášení

Prohlašuji, že předložená diplomová práce je původní a zpracoval jsem ji samostatně. Prohlašuji, že citace použitých pramenů je úplná, že jsem ve své práci neporušil autorská práva (ve smyslu Zákona č. 121/2000 Sb., o právu autorském a o právech souvisejících s právem autorským).

V Brně dne 29. května 2015

……………………

Petr Volf

Poděkování

Na tomto místě bych rád poděkoval panu prof. Ing. Petru Dostálovi, CSc. za trpělivost, věcné podněty a odborné vedení této práce. Také bych rád poděkoval své rodině, která mě podporovala během studií.

Obsah

1. Introduction

This master thesis focuses on the topic of trading on commodity markets. Commodity markets were chosen mostly because of their increasing popularity and because of the interesting earning that are possible to be achieved when trading the commodities. It is mainly due to the leverage existing there. It is possible to earn much more money by trading the commodities or other futures, than by trading stocks. Of course it is also riskier, but with the right money management and responsible approach, a trader can make quite good money by trading leveraged instruments.

The other reason for this topic was the fact that in spite of increasing number of commodity traders, there are not many academic papers focusing on this part of the financial markets. Most of the academic work is focused on stocks.

The thesis is structured in a way of introducing the reader to the problem of trading and artificial intelligence in the theoretical part and then demonstrating the theoretical background in the real life situation further in the solution part. The solution is designed to predict the price of Live Cattle commodity based on its historical prices. At the end of the solution chapter there is a summary of the findings with the best options of the problem solution highlighted.

The neural network is designed, trained and then used for prediction using the MATLAB program, specifically MATLAB R2015a. After reading the thesis, the reader should be able to design their own investment strategy using the MATLAB code, which was generated as part of the solution.

2. Goals, methods and process of implementation of the thesis

2.1 Goals of the thesis

The main goal of this thesis is to design a universal solution that would help commodity traders with their investment decision. MATLAB will be used to develop a program code that could be used to predict future values of any commodity. The requirement is for the solution to be more successful (have better probability) than 50%. If the success rate of the prediction is lower than 50%, the solution does not help the investment decision more than flipping a coin.

2.2 Methods used within the thesis and solution process

The selected commodity is Live Cattle, for which the historical prices were acquired using a trial account on the CSI Unfair Advantage® trading platform. The prices were gathered for the time period of 1 October 2013 to 22 May 2015, but the historical prices range was selected for the past 8 months after analyzing the price trend. As mentioned above, the program used is MATLAB R2015a, so to ensure full compatibility of the code, the reader should use the same version.

3. Theoretical background

This part of the thesis is focused on the information necessary for design of a solution for the examined matter further described in the chapter about Analysis of the current state. The theoretical information forms a basis for the analysis and design of a solution in the upcoming chapters.

3.1 Financial Markets

Financial market is a broad term that can have several meanings, but generally speaking it means any marketplace where the trade of various assets, such as bonds, equities, currencies, derivatives, is carried out between buyers and sellers. The financial markets are thought of as transparent, regulated, and with market forces determining the prices of securities that trade (Investopedia, 2015c).

Investing in financial markets is a great way of saving money, people can choose to invest into certain type of instruments based on their approach. If they are in their twenties or thirties, need to accumulate funds quickly for using the return in the upcoming years and can take on the risk of losing some money, they may choose an aggressive approach where their portfolio would consist of riskier instruments with the possibility of higher return. If an investor is older, want to save for their retirement and cannot afford to lose their capital, they might choose low risk instruments with steady and reliable growth.

The problem is that people still don’t trust the financial markets and are scared of investing in them. Especially after the financial crisis in 2009, when for example the popular S&P 500 (Standard & Poor's 500) and Dow Jones (Dow Jones Industrial Average) stock market indexes traded at less than 50 % of their value in 2007 (Cheng, 2011).

Fink suggests in his article about restoring confidence in the financial markets: “Financial education and transparent investment products that are easy to understand and apply can allow investors to capture market opportunities and achieve the returns they need to achieve their objectives even in a complex and challenging new world. This too will help restore trust in the markets, and help those who doubt in the future today take their first steps back to being investors again” (2012).

3.2 Trading

When we are talking about trading, first of all it is important to realize what trading is. It is often confused with “investing”. But the terms trading and investing are not interchangeable and do not have the same meaning. As Hartman (2013) describes, it is possible to invest various things, not just your finances (e.g. time) and you can invest pretty much into anything – real estate, cars, lands, financial instruments and all sorts of things. Investing is more of a general term, whereas trading if focused on a particular activity.

Another difference between those two is the time interval they are related to – investing is usually a matter of long-term process, but in trading you are mostly dealing with short-term actions. Traders are much more active than investors. With the right time and money management, they are also likely to achieve higher profit in a shorter period of time (Hartman, 2013).

On the other hand, trading is also riskier than investing in most cases, only person with the right training and experience, a person who knows what to do, should start this business. The Pareto principle applies here – Nesnídal (2007) claims that 80 % of traders finish unsuccessfully within 5 years. Although according to Nesnídal (2007), the Pareto principle can further be found in the profit situation as 80 % of profit is generated by 20 % of trades (Investopedia, 2015a).

3.2.1 Overview of instrument types

There are many different financial instruments an investor or a trader can invest in. Further in this chapter there is a list of the mostly used ones with a brief description of each.

3.2.1.1 Stocks

Stock, also often referred to as “shares” or “equities”, represents ownership in a company, which applies to the company’s earnings and assets. The holder of the company’s stock is called a shareholder and his share of the company is derived from the number of shares he owns compared to the total of outstanding shares. There are two different types of shares – committed and preferred. The first one usually gives the owner the voting rights at shareholders' meetings and a claim on dividends. The latter is usually not entitled with voting rights, but has a higher claim on the company's assets and earnings (Investopedia, 2015i).

3.2.1.2 Bonds

Bond, commonly referred to as fixed-income security, represents a debt investment in which an investor lends money to an entity (usually a corporation or governmental institution), which borrows the funds for a specified period of time at a fixed or variable interest rate. The owner of a bond, the investor who lends the money, is called a debtholder, or a creditor, and the entity borrowing the money is the one which issues the bond, hence called an issuer. Corporate and government bonds are often traded on exchanges, other bonds are traded OTC, which means over-the-counter (Investopedia, 2015b).

3.2.1.3 Mutual Funds

Mutual fund is a financial instrument consisting of pool of funds collected from many investors. The fund is managed by money managers, or fund managers, who use the accumulated money to invest in other securities such as stocks, bonds, money market instruments and other assets. The idea behind mutual funds is that using a bigger amount of money it is possible to have a diversified portfolio of instruments and compared to investing in single shares or bonds, this option has a lower risk and usually stable interest rate. The advantage for investors is that the managed fund is taken care of by professionals and the investor doesn't have to spend time watching the market trends and financial news to be able to decide which equity to invest in. The mutual funds differ from each other by the approach investors prefer – there are more aggressive funds where it is possible to achieve greater earnings, but with higher risk of loss. On the others side of a mutual funds spectrum, there are conservative funds offering lower earnings, but stable with a small risk of loss (Investopedia, 2015g).

A market value of a mutual fund is determined by the Net Asset Value (NAV). It is a price at which the fund shares can be bought ("bid price") by investors from a fund company and at which the shares can be sold ("redemption price") to the fund company.

NAV is computed at the end of each trading day and the value is derived from closing market prices of the portfolio's securities (Investopedia, 2015j).

3.2.1.4 Exchange Traded Funds

Exchange Traded Fund (ETF) is similar to mutual fund with the difference that it is traded on a stock exchange. ETF owns the underlying assets (shares, bonds, foreign currency, etc.) and the ownerships is then divided into shares. The price of ETFs changes throughout the day as it is bought and sold, just like it is with equities on a stock exchange. Compared to mutual funds, the ETFs have usually higher daily liquidity and lower fees, which makes them an interesting option for individual investors. ETFs combine the advantage of diversification of an index fund and the ability to sell short, buy on margin and purchase as little as one share of the ETF (Investopedia, 2015d).

3.2.1.5 Options

Options belong to derivatives as their value is derived from the value of the underlying assets. It is a contract between two parties – an option seller (option writer) and an option buyer (option holder). The option gives its holder the right, but not the obligation, to buy (call) or sell (put) a security or other financial asset at an specified price (the strike price) during an agreed period of time or on a certain date (exercise date). Options are used for speculation about the price trend of the underlying assets (Investopedia, 2015h).

3.2.1.6 Futures

The history of futures trading as we know it today goes back to 1848, when the Chicago Board of Trade was opened as a market for Midwest farmers. Futures contracts were introduced back then in order to balance the supply and demand of grain and others commodities, and stabilize their prices. With the aim of providing stable supply of grain for a stable price throughout the year, as Waldron (2003, p. 19) describes, "prices in effect at delivery time would have been agreed to many months beforehand, and contracts signed."

Futures represents a financial contract that obligates the buyer to purchase an asset (or the seller to sell an asset) at predetermined price and date. Such assets can be a physical commodity or a financial instrument. The main feature of the futures markets is the ability to use very high leverage relative to stock markets (Investopedia, 2015f).

3.2.1.7 Hedge funds

Hedge funds are very similar to mutual funds, although it is not easy to define hedge funds. As Garbaravicius and Dierick (2005) from the European Central Bank state, “there is no common definition of what constitutes a hedge fund, it can be described as an unregulated or loosely regulated fund which can freely use various active investment strategies to achieve positive absolute returns.”

Mitra (2009) follows up on the statement from European Central Bank suggesting a way of defining a hedge fund by comparing the similarities and differences with mutual funds. There are three aspects in which the hedge funds are similar to any other portfolio investment:

- Rather than being funded by bank loans and similar sources of capital, they are funded by capital from investors.
- They invest in publicly traded securities, such as equities and bonds.
- The capital invested and managed by expert fund managers

“The key differences between Hedge Funds and Mutual Funds lies in the degree of regulation, the level and variety of risky investment strategies. Whereas Mutual Funds are required to adhere to strict financial regulations, including the types and levels of risks, Hedge Funds are free to pursue virtually any investment strategy with any level of risk” (Mitra, 2009, pp. 3-4).

3.3 Trading analyses

3.3.1 Fundamental analysis

“Fundamental analysis is about using real data to evaluate a security's value. Although most analysts use fundamental analysis to value stocks, this method of valuation can be used for just about any type of security.

For example, an investor can perform fundamental analysis on a bond's value by looking at economic factors, such as interest rates and the overall state of the economy, and information about the bond issuer, such as potential changes in credit ratings. For assessing stocks, this method uses revenues, earnings, future growth, return on equity, profit margins and other data to determine a company's underlying value and potential for future growth. In terms of stocks, fundamental analysis focuses on the financial statements of the company being evaluated.

One of the most famous and successful fundamental analysts is the Oracle of Omaha, Warren Buffett, who is well known for successfully employing fundamental analysis to pick securities. His abilities have turned him into a billionaire” (Investopedia, 2015e).

3.3.2 Technical analysis

The practice of using statistics to determine trends in security prices and make or recommend investment decisions based on those trends. Technical analysis does not attempt to determine the intrinsic value of securities, but instead focuses on matters such as trade volume, demand, and volatility. Technical analysts evaluate short-term trends almost exclusively, which is both a strength and a weakness in their analysis. They are sometimes called chartists because of the importance charts have in technical analysis (Dictionary, 2015).

“Technical analysis is the attempt to predict future market prices by studying past prices, based on a number of theories concerning the recurrence of particular patterns in market activity.

Technical analysts will seek to identify well-known patterns in the price chart, to establish the support and resistance levels for price trends, and to gauge the likely continuance of established trends using a range of technical indicators.

Some traders will combine technical analysis with a study of fundamentals or breaking news, while others will focus solely on the study of prices. Either way, you will need flexible charting software to conduct your price analysis" (InterTrader, 2015).

3.3.2.1 Technical indicators

This chapter lists the technical indicators used in the analysis part of the thesis:

- RSI (Relative Strength Index)
- Moving Average (Simple, exponential)
- A/D line (Accumulation/Distribution line)
- ROC (Price Rate of Change)

3.3.3 Psychological analysis

Psychology is one of the most important aspects of trading – if a trader wants to be successful, they need to be able to control their emotions. You can have the best information and perfectly worked out technical analysis, but if you panic and act without thinking things through, it may cost you a lot. As Shipman (2007) suggests, it is important to stick with your strategy and be disciplined about your decisions. Every trade should be entered with a plan and if you as a trader rationally plan to close a trade at a certain point, you need to do so when that situation occurs and not let the market and decisions of others affect your own plan.

Garner (2014) introduces in his publication a theory about three main emotions, which can affect the trading capabilities. Those are: *fear*, *greed* and *frustration*.

Fear

The things speculators / traders **fear** are usually common for most of them, regardless of what kind of markets they trade on. They fear losing the money, they are afraid of misjudgment or missing out on an opportunity. But fear is good, it is a vital emotion that keeps us aware of dangers we may encounter. Without fear, people would not be afraid of taking on high risks and engaging in trades with high possibility of failure (Garner, 2014).

Speculators should enter every market they intend to trade on with respect. They should have a sound lever of fear to stay alert. Controlled fear of losing money can help them to remain objective and think their trades through. On the other hand, those who fear anything that might affect their trades, they are prone to making rushed and irrational decisions. There are various sources of fear in trading, but one of the main ones is the decreasing balance on the trader's account – those with low capital usually trade timidly and therefore their results are usually worse. Also because of the fact that with low capital on their trading account, they have little space to correct any judgmental errors from before (Garner, 2014).

Greed

Greed is a crucial emotion, which makes the traders to enter the markets with the vision of achieving high earnings compared to keeping their money in savings account or similar possibilities generating very little interest. Besides great amount of opportunities that arise on the financial markets thanks to human greed, this emotion on the other hand brings also misery and suffering (Garner, 2014).

Greed inside of most traders works in two directions. Before they even enter a position, their goal is to make the highest profit. But if they enter a trade and the trend does not go on as we expected, the desire for achieving a profit suddenly turns into a need of being right, or at least not being too wrong and losing money. At this moment the greed for a quick and high profit changes to a need of not hurting their ego. But ego is the problem, there is no space for ego in trading. Traders should be able to admit they were wrong, exit their trade position and put up with the small loss, before the loss gets too big to recover from (Garner, 2014).

Frustration

The influence of frustration on the results of traders is often overlooked. Although the ability not to let the disappointment affect our judgment is very important. One might even say it is one of the main differences between successful and unsuccessful speculators (Garner, 2014).

There are two main scenarios, in which the frustration can occur – closing a losing trade or closing a profitable trade too soon to for the trader to only find out how much more money they could have made if they had left the trade open for a bit longer. In these cases, when a traders for example enters a short position with the price at 70,60 USD and a stop loss order at 71,80 USD, it may be very frustrating when the price goes up and reaches the set stop loss, only to change direction immediately and decrease down to e.g. 67,60 USD. The traders then often do not consider as a loss only the money they have actually lost, but also the amount they did not earn due to triggered stop loss order (Garner, 2014).

3.4 Understanding the trading charts

"Charts are crucial for a trader to be able to determine when to enter a long or short position and when to exit the position. It is therefore vital to understand the chart completely.

A chart provides a simple way to visualize and analyze historical prices for a particular market, and the way those prices have changed over time. Whatever trading strategy you use, you need to understand price behavior in your chosen market before you start to trade. A price chart helps you do that (InterTrader, 2015).

Modern charting packages allow traders to visualize price activity in different forms. Three of the most common types are bar charts, candlestick charts, and line charts. These chart types are based on the same price activity, but different aspects of the trading data are emphasized in each case.

In a **bar chart**, the open, close, high and low prices of a given time period are displayed: each bar extends from the low to the high for the interval with a left-side spur showing the open and a right-side spur showing the close (last price during this interval). This allows traders quickly to identify whether prices rose or fell over the interval.

Figure 1: Bar chart (InterTrader, 2015)

Candlestick charts are similar but with one key difference: the space between the open and close is filled and coloured to show whether the interval had a positive or negative close. A wick extends at the top and bottom to the high and low for the interval. Candlestick charts allow different types of price pattern to be identified and are commonly used by traders with shorter-term strategies.

Figure 2: Candlestick chart (InterTrader, 2015)

Line charts (or tick charts) remove the open, high and low price data and only show the last price traded during the interval. Prices appear as a simple line graph. This type of chart is often used by news traders on intraday timeframes where in-depth technical analysis is not utilized" (InterTrader, 2015).

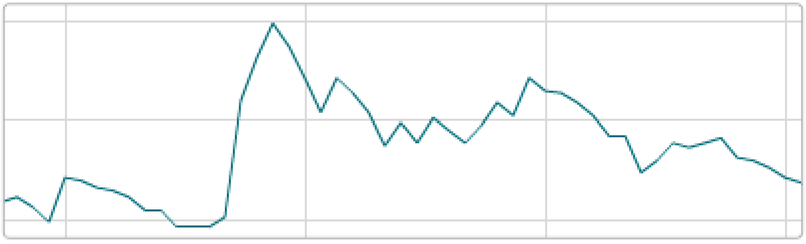

Figure 3: Line chart (InterTrader, 2015)

3.5 Advanced decision making analyses

There are several analyses available for advanced decision making, like fuzzy logic, genetic algorithms, chaos theory, and so on. Since only Artificial Neural Networks are used within this thesis, this analysis will be described below.

3.5.1 Artificial neural network

The artificial neural networks represent in a certain way thinking of the human brain. The model of neural network is often referred to as a "black box" as it is not possible to know exactly the inside structure of the system. We make only certain assumptions, but the rest is carried out inside the “black box”. The use of neural networks is suitable in situations where in influences of the examined phenomena are random and deterministic relations are complicated (Dostál, 2011).

The biological neuron can by simply presented in a form that consists of many inputs (dendrites), body (soma), and one output (axon) as shown in **Figure 4**. Together they comprise the basic building blocks for biological brains (Dostál, 2011).

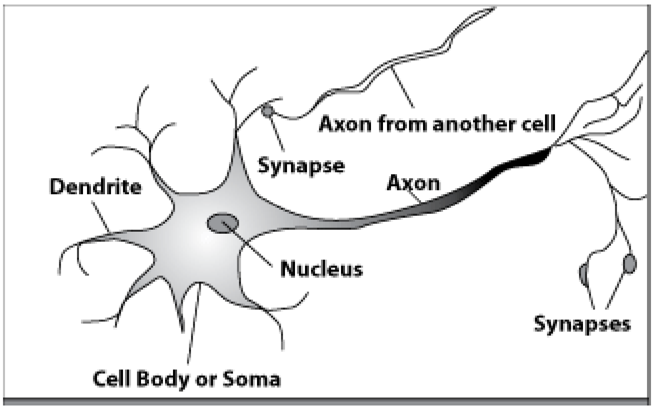

Figure 4: Biological neuron (NeuralPower, 2015)

“The development of artificial neural networks was initially motivated by insights into how biological brains – and in particular, mammalian brains (natural neural networks) – function. To simplify, mammalian brains learn as connections between neurons are strengthened – the result of electrochemical processes triggered by external or internal stimuli ("experiences").

Similarly, Artificial Neural Networks consist of many interconnected artificial neurons – sometimes referred to as Processing Elements (PEs). Artificial neural networks can be designed to implement either supervised or unsupervised learning. With supervised learning, the learning (modeling) objective is to map a set of input (independent) data values to an associated output (dependent) data value. The supervised learning process is the equivalent of fitting a complex mathematical formula to a curve, yielding models which generalize well and which can be employed in a wide variety of prediction and classification tasks. With artificial neurons which implement supervised learning, thresholds are modeled by activation functions and reinforcement is modeled by non-linear transfer functions. A typical neural network uses sigmoid or hyperbolic transfer functions – which are non-linear in their response to inputs and differentiable.

During supervised training, the back propagation algorithm uses calculus methods to distribute ("propagate") errors at the output layer backwards through the network until the input layer is reached. The learning (adaptation) power of neural networks stems from capabilities that emerge when many artificial neurons are connected" (NeuralPower, 2015).

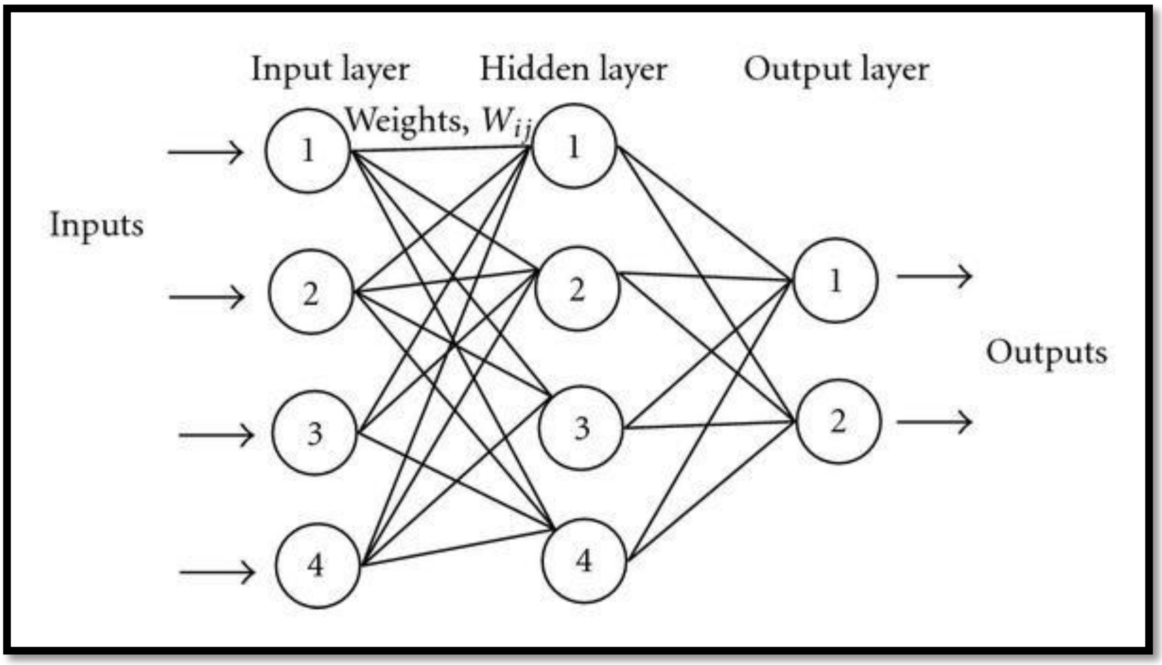

Figure 5: Example of artificial neural network (Corporation, 2015)

4. Analysis of the current state

Trading commodities in known to be built mainly on the grounds of technical analysis. The fundamental analysis is not used very often by regular commodity trader as it is considered that all the significant changes incurred by the external elements are already included in the price as the market is influenced by the large investment companies and other big players on the market and by the time the information gets to the regular trader, the price has already moved and the trader cannot react on the change by placing appropriate orders. Also the trading of commodities is often intraday, so there is really not much time to get to know all the details of an expected price movement before placing an order.

So the technical analysis is the main tool used in the commodity markets these days. Since we are living in a fast-paced world, there is always a demand for tools that would save us some time and make our life easier. Most of the commodity / futures contract traders spend a lot of time on the internet looking for a guaranteed strategy how to trade. They are looking for answers to their question of when to enter a position, what direction will the price take, what trend it will create, for how long to remain in the open position before closing it, so that the profit is the highest. In such situations there is a high demand for the right commodity to choose, the right period of the chart and the right technical indicator to display on the chart.

When there is such demand, it offers an opportunity to find a solution for such problem. As a subject, which can use the suggested solution in times of shortage of the cash to fund successful running of a firm, the FNZ company was chosen. A brief introduction follows.

4.1 Introduction of the firm

FNZ is a world leader in the design, build and support of platforms for the financial and wealth management markets. FNZ was founded as a start-up in 2004 in New Zealand and evolved into a global company with branches all over the world: London, Edinburgh, Bristol, Brno, Sydney, Wellington and Hong Kong. The branch in Brno was opened in 2010 and there are currently 2 offices in Brno, which are slowly being transformed into a biggest branch.

FNZ offers various financial platforms (advised, direct to customer, corporate, etc.) and is able to meet high requirements from their clients. The platforms developed by FNZ are capable of management of various types of accounts and products. It can be used to manage savings account, pension product, investment portfolio, junior account, etc. The company is best known for the speed of software development and delivery, thanks to which they are often preferred by the customers over FNZ’s competitors.

5. Proposed solution

This is the main part of the whole thesis, where it is described how in reality neural networks work and how we can use them in trading. Factual examples of price prediction using neural network developed in MATLAB are demonstrated further in this chapter. This chapter is divided into two main topics: NAR and NARX. Those represent two different models of neural networks used for prediction, each will be described further.

The data used within the section, for which future values will be predicted, is a Live Stock commodity futures value. Based on the trend of the price of Live Stock, a subset of values was selected – the historical data used for training, validation and testing of the neural network is a range of daily price from 15/08/2014 to 15/04/2015. An example of the data is shown in **Table 1** below.

Table 1: Example portion of the used data (Source: designed by the author)

Date	Open	High	Low	Close	Volume
1.10.2014	163,84016	166,02582	163,55205	165,87869	15995
2.10.2014	165,65123	166,97172	165,56066	166,29467	9584
3.10.2014	166,35369	167,60861	165,51434	165,58730	9206
6.10.2014	165,88320	166,81475	165,45328	166,11311	7946
7.10.2014	166,06844	168,44836	165,81721	167,04180	10835
8.10.2014	167,12705	168,09959	166,23033	167,61475	7549
9.10.2014	167,93566	168,91148	164,60738	166,39139	11990
10.10.2014	165,77500	166,40000	164,05000	165,00000	8475
13.10.2014	165,61102	166,96949	165,49237	165,99492	5038
14.10.2014	166,08644	166,29153	163,27288	163,55254	7556
15.10.2014	163,80763	164,23051	160,90678	161,42712	10385
16.10.2014	161,87288	164,07966	161,31017	163,93220	7803
17.10.2014	163,44958	164,00551	162,41314	163,79068	5788
20.10.2014	163,70297	166,69025	163,68220	166,53983	6994
21.10.2014	166,32246	168,03686	165,05169	165,78898	9135
22.10.2014	165,69492	167,28390	165,45000	167,24873	6813
23.10.2014	167,20890	169,08136	166,80805	168,45339	8395
24.10.2014	168,58263	168,94915	165,64661	166,12881	4889
27.10.2014	166,24534	167,83136	165,85678	167,53856	5435
28.10.2014	167,26398	167,44322	166,13347	167,11271	4935
29.10.2014	166,94873	167,54958	165,71144	166,78729	8980
30.10.2014	166,46356	167,85593	166,28178	167,03432	9803
31.10.2014	167,00339	167,42627	165,31144	165,92203	10101

The 8 months (15/08/2014 – 15/04/2015) of daily prices of Live Cattle are used for prediction of the price for the next day. The solution is best suited for a daily trader who wants to know the trend of a selected item for the next day.

5.1 NAR (Nonlinear Autoregressive) network

NAR is a neural network capable of predicting series $y(t)$ based on n values of $y(t)$, only one series is involved in this type of network. So the network is then defined by the following formula:

$$y(t) = f(y(t-1), \ldots y(t-n))$$

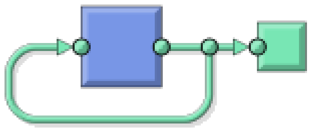

Figure 6: Diagram of general NAR network (Source: MATLAB R2015a)

There are several steps a user needs to go through during the setup of the NAR network, these steps are described in the following text.

Generally speaking the first step in setting up a neural network is defining the problem the selected neural network would be solving. In this case, as mentioned above, the problem is a prediction of future price of the Live Cattle commodity, based on its historical prices. Close price series (target data/timesteps) is used in this network and the prediction is designed for 1 day in the future. For example, the close price of Live Cattle on 15 April 2015 was 149,1108 and the NAR network would be run, with a series of prices ending with the price of 15 April, to predict the close price of the next day, therefore in 16 April 2015 in this example.

5.1.1 Parameters of the NAR network

Once the problem is defined and data acquired, it is time to set the parameters of the network in order for the program to perform well and give the best results. This part is fundamental for a successful result of the network. See the CD, which is attached to this thesis, for the files with the code and change the undermentioned parameters according to your problem you are seeking a solution for. The file with the code of NAR network is called "*NAR_Network.m*"

Number of delays

As defined in the MathWorks documentation (2015), the NAR network represents a two-layered feedforward network, with a linear transfer function in the output layer and sigmoid transfer function in the hidden layer. The network uses tapped delay lines for storing the previous values of the $y(t)$ sequence. The $y(t)$ output of the NAR network is fed back to the input of the network through delays, since $y(t)$ is a function of $y(t-1), y(t-2), \ldots, y(t-n)$.

The number of delays was left at default value of 2 for this network as when tested, the network performed well. The network is created and trained in open loop form.

Number of hidden layer neurons

The number of neurons in the hidden layer is the main parameter that is changed within this solution in order to provide better results. 10, 20, 50 and 100 neurons in the hidden layer were used and tested with the NAR network. For each option the results were noted down and are discussed further in this chapter.

Data division

The source data (target data) used for the network must be divided into subsets – subset for training, validation a testing of the network.

- *Training* data are presented to the network during training, and the network is adjusted according to its error – this was left at default 70 %.
- *Validation* data are used to measure network generalization, and to halt training when generalization stops improving – this timestep subset was left at default 15 %
- *Testing* data have no effect on training and therefore provide an independent measure of network performance during and after training – this was, as well as validation, left at default part of 15 % (MathWorks, 2015).

There are several functions that can be used for dividing the data series into 3 subsets:

- *dividerand* – this is the most common function for data division and is also used as default in MATLAB. *Dividerand* divides the data randomly into 3 subsets used for training, validation and testing.
- *divideblock* – using this function, the data gets allocated to three subsets using three contiguous blocks of the original data set (training fitting the first block, validation the second and testing the third).
- *divideint* – this function divides the data by an interleaved method, as in dealing a deck of cards. It is carried out in a way that different percentages of data go into the three subsets.
- *divideind* – the last function uses indices for the data division. The indices for the three subsets are defined by the following division parameters:
    - *net.divideParam.trainInd*
    - *net.divideParam.valInd*
    - *net.divideParam.testInd*

  Null array is the default assignment for these indices, so these parameters must be set when using the *divideind* function (MathWorks, 2015).

Training algorithm

There are 3 different algorithms to choose from for the network training:

- Levenberg-Marquardt (*trainlm*) – this algorithm is recommended for most problems and is also selected as default in MATLAB. It updates weight and bias values based on Levenberg-Marquardt optimization. Out of the 3 training algorithms, this one is often the fastest backpropagation algorithm.
- Bayesian Regularization (*trainbr*) – this algorithm is usually a better option for some noisy and small problems. It can take longer, but should provide better solution. It also updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights. The correct combination is then determined in order to produce a network that generalizes well. This process is called Bayesian regularization.

- Scaled Conjugate Gradient (*trainscg*) – this one is recommended for larger problems, because it uses gradient calculations which use less memory than the Jacobian calculations used in the previous two algorithms (MathWorks, 2015).

Neural Network Performance Function

There are various performance functions a user can select from:

- Mean squared error (*mse*) – the mostly used performance function, which measures the network's performance according to the mean of squared errors.
- Mean absolute error (*mae*) – measures network performance as the mean of absolute errors.
- Sum absolute error (*sae*) – this function measures performance according to the sum of squared errors.
- Sum squared error (*sse*) – measures performance according to the sum of squared errors (MathWorks, 2015).

5.1.2 Run of the NAR neural network

This chapter is focused on the run of the NAR network itself with the description of the individual steps taken to prepare the network to perform well. There are several ways of how a user can tell if the network is trained correctly and hence should generate accurate results. These ways are described in detail further in this chapter.

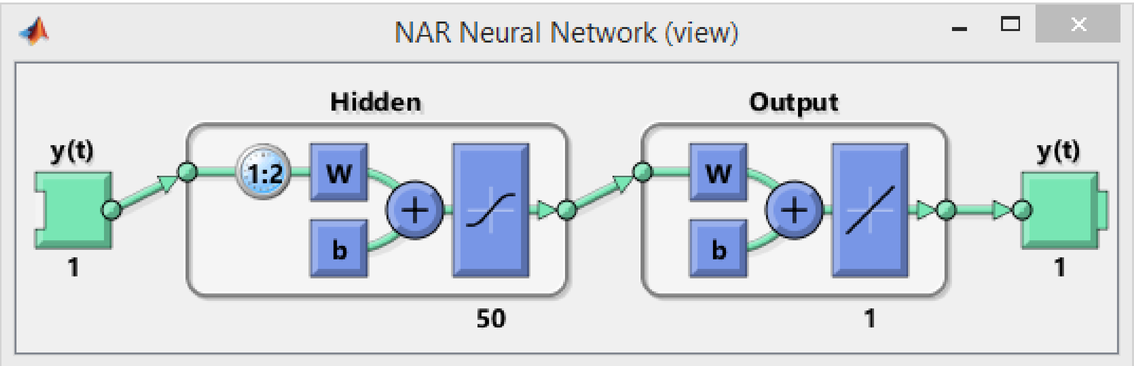

Figure 7: Diagram of the NAR network (Source: MATLAB R2015a)

As shown on the diagram in **Figure 7**, the number of delays for this network is set to 2 and the number of neurons in the hidden layer is set to 50. It is also evident that the network uses sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The network is created and trained in open loop form. Open loop (single-step) method is more efficient for training than the closed loop (multi-step) one. Open loop process can be used, because true output is available during the training and the true output is used here feeding back the estimated output. The advantage is that the input to the feedforward network is more accurate and the resulting network is a purely feedforward architecture, hence a more efficient algorithm can be used for training (MathWorks, 2015).

When the code from the CD attached to this thesis is run in MATLAB, the following figures and diagrams are shown. The figures below are all generated by a network with 50 neurons in the hidden layer.

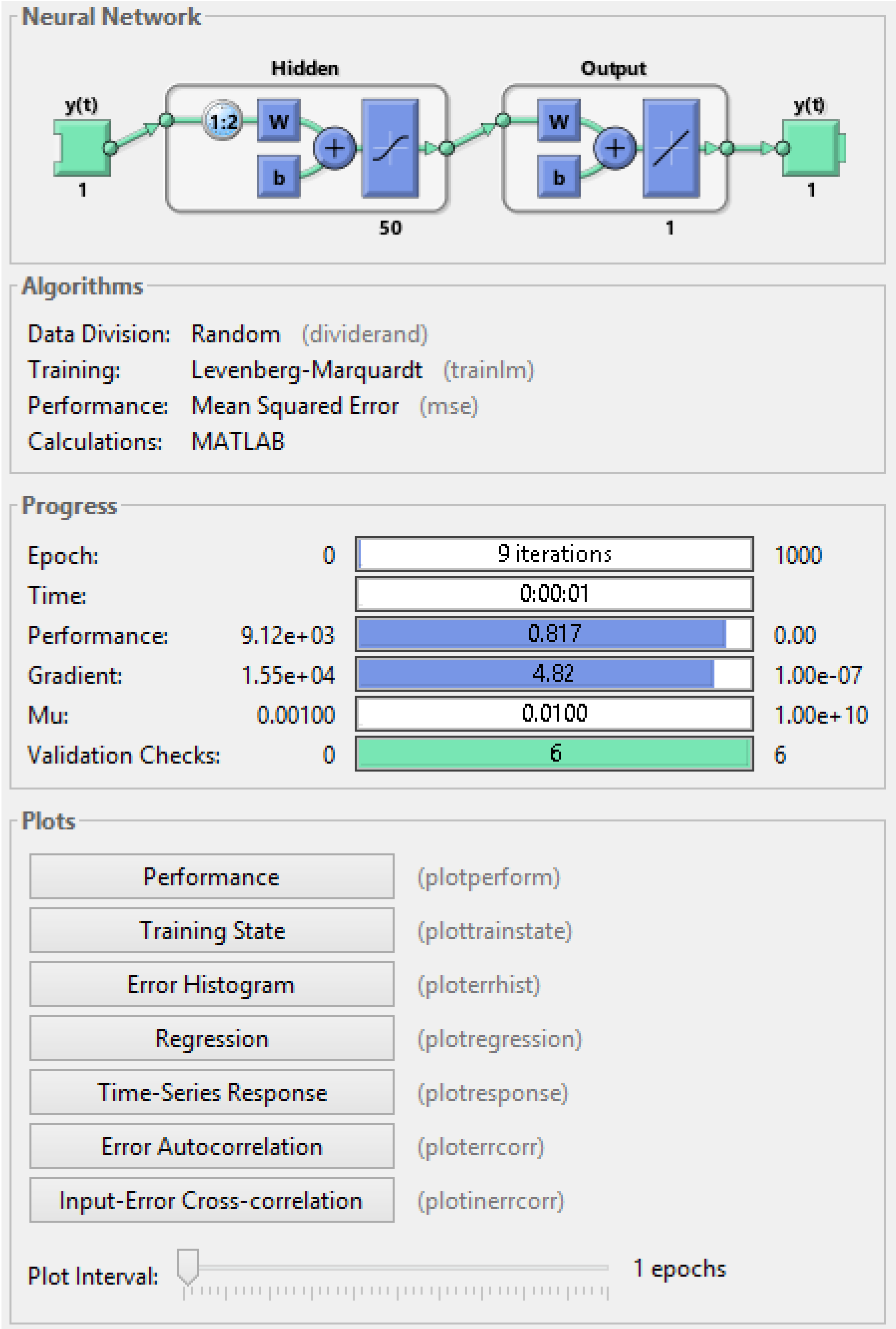

Figure 8: Training of the NAR network (Source: MATLAB R2015a)

In **Figure 8**, the training parameters of the network are displayed as well as the training results. It is apparent that data were divided randomly, Levenberg-Marquardt training algorithm was chosen and Mean Squared Error was used as the performance function. According to the training results, the training continued until the validation error failed to decrease for 6 iterations (validation stop).

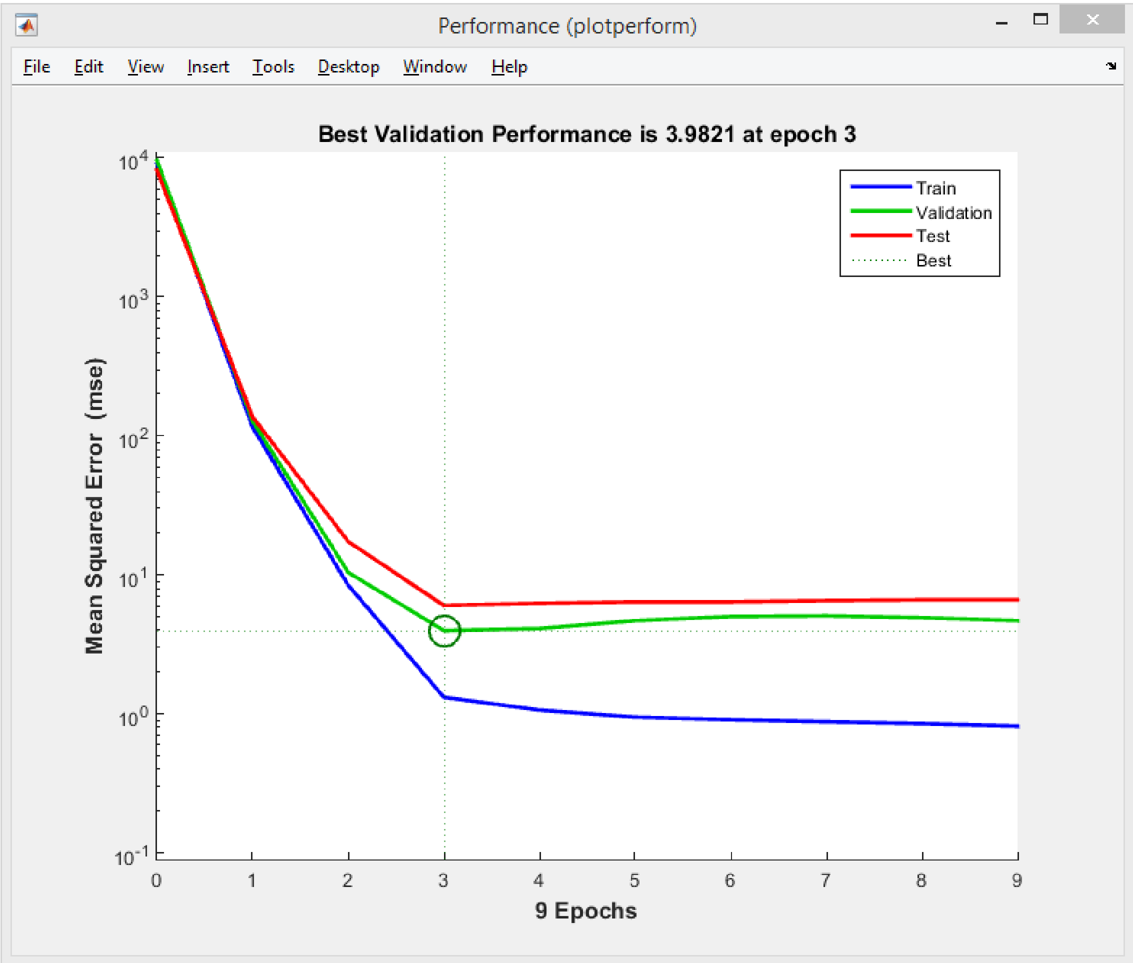

Figure 9: NAR Performance Training Record (Source: MATLAB R2015a)

The performance training record is plotted in **Figure 9** in order to check for potential overfitting of the network. The figure shows that the training, validation and testing errors all decreased until iteration 3, where the validation error reached its minimum of 3,9821. Since neither testing, nor validation increased before iteration 3, it does not seem that any overfitting has occurred (MathWorks, 2015).

The following plot in **Figure 10** below displays the error autocorrelation function. It describes how the prediction errors are related in time. For a situation with perfect prediction model, there should only be one nonzero value of the autocorrelation function, which would occur at zero lag, which is the mean square error. That would imply that the prediction errors were completely uncorrelated with each other (white noise).

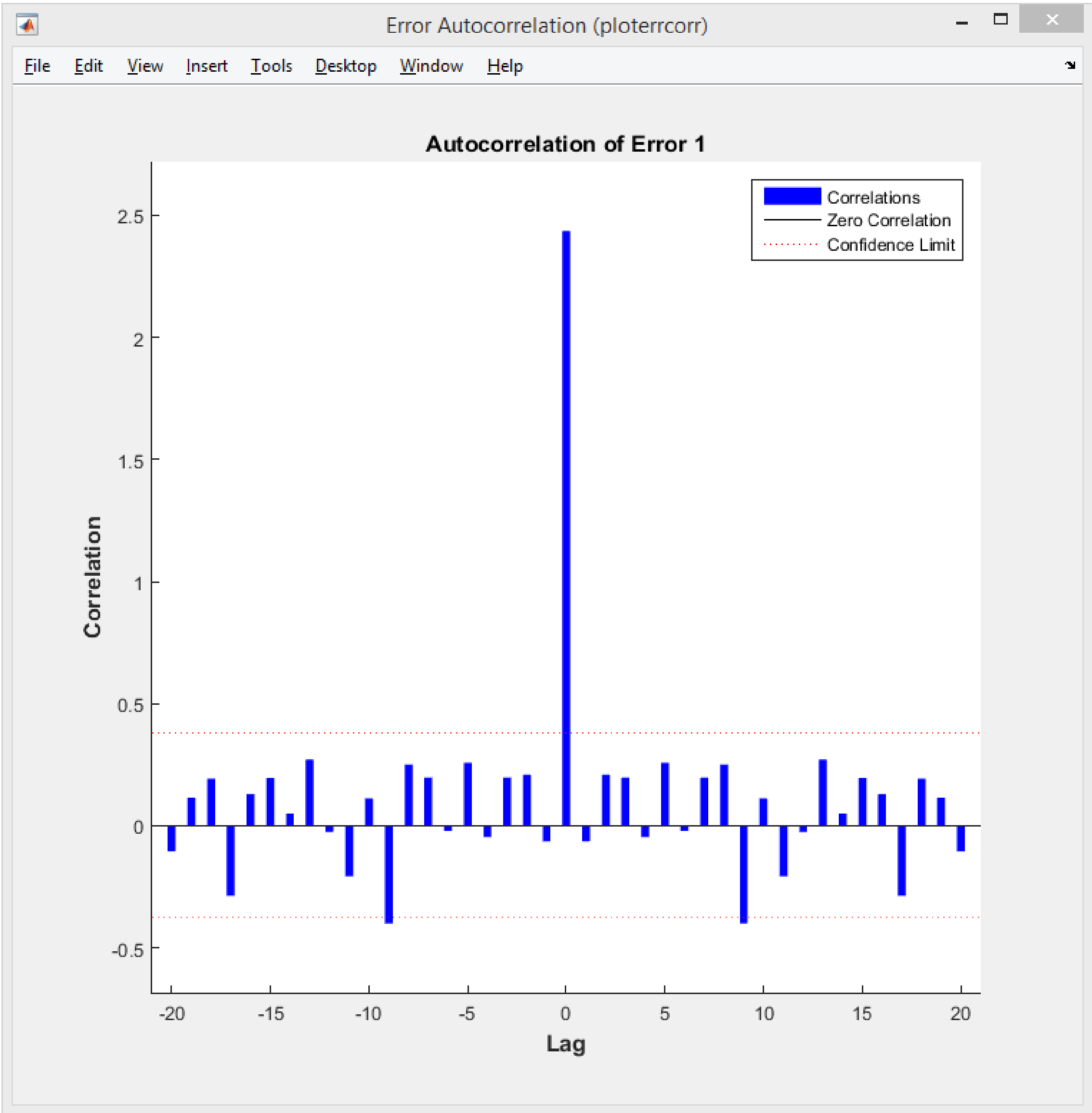

Figure 10: NAR Error Autocorrelation (Source: MATLAB R2015a)

In this case, except for the one at zero lag, the correlations fall approximately within the 95% confidence limits around zero, so the model seems to be adequate. If there was significant correlation in the prediction errors, it should be possible to improve the prediction, for example by increasing the number of delays in the tapped delay line. Another option would be to retrain the network – this would change the initial weights and biases of the network and could produce an improved and more accurate network after retraining (MathWorks, 2015).

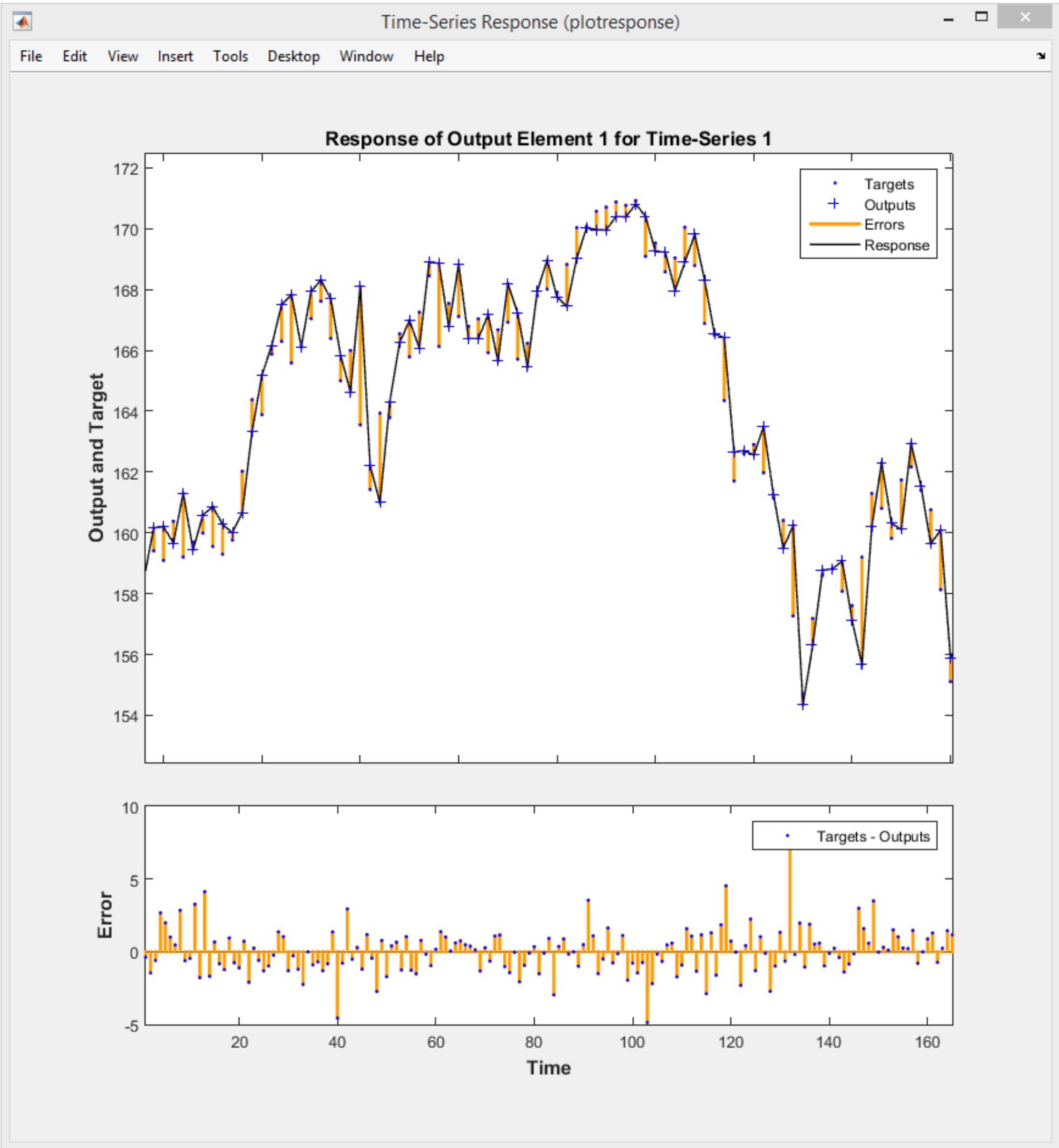

Figure 11: NAR Time-Series Response (Source: MATLAB R2015a)

The plot in **Figure 11** displays the targets, outputs and errors versus time. It is apparent that the training generated an output values that differ from the targets approximately by no more than around 2 in most cases. The plot is zoomed in, capturing just a portion of the whole plot in order to display the details better.

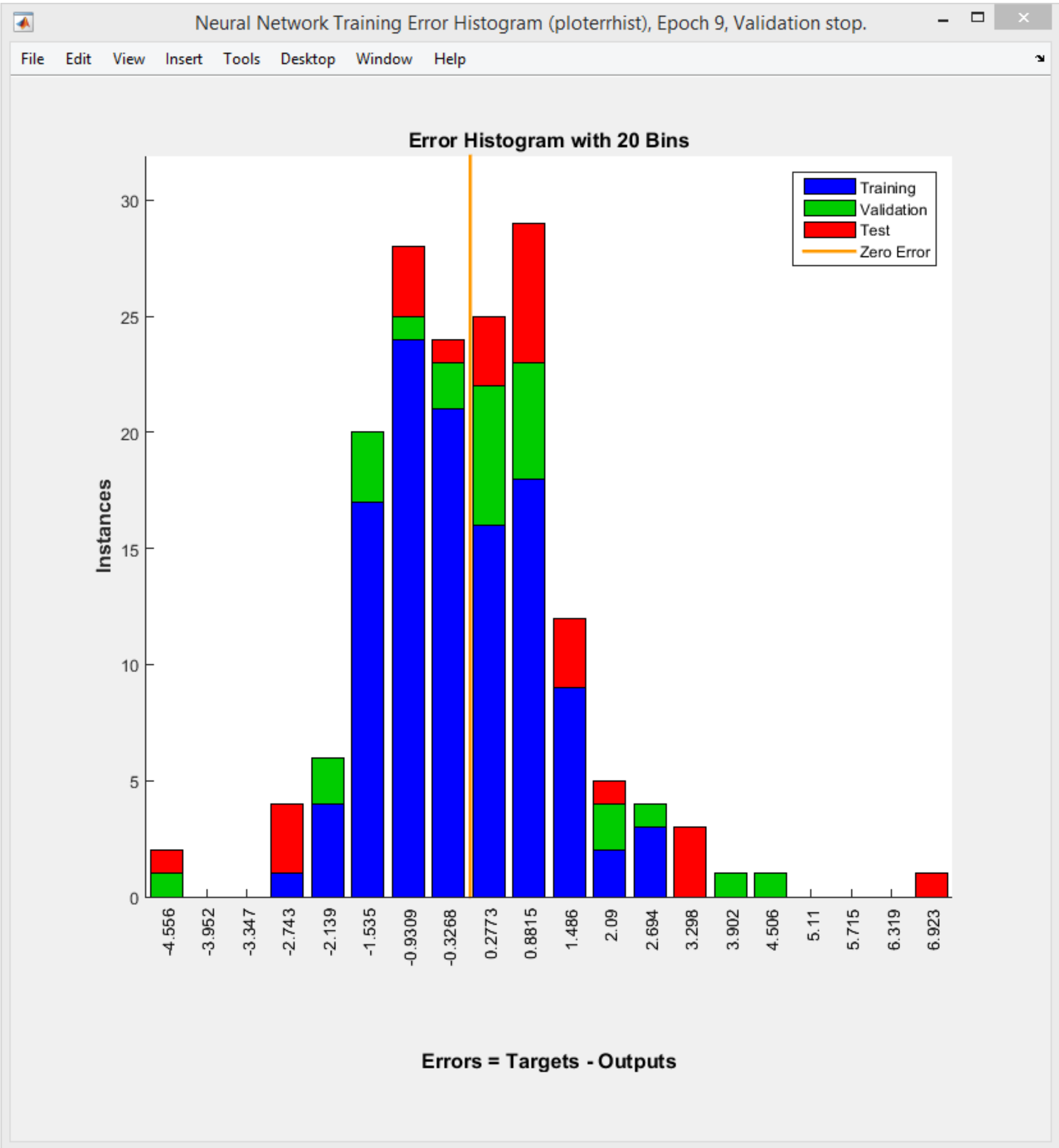

Figure 12: NAR Error Histogram (Source: MATLAB R2015a)

Another plot for the NAR network is the error histogram displayed in **Figure 12**, where it is possible to determine how large the errors are, therefore the most common difference between the targets (the historical values) and the outputs (the predicted values). It is also distinguished if the errors are connected to the training, validation or the test data subset.

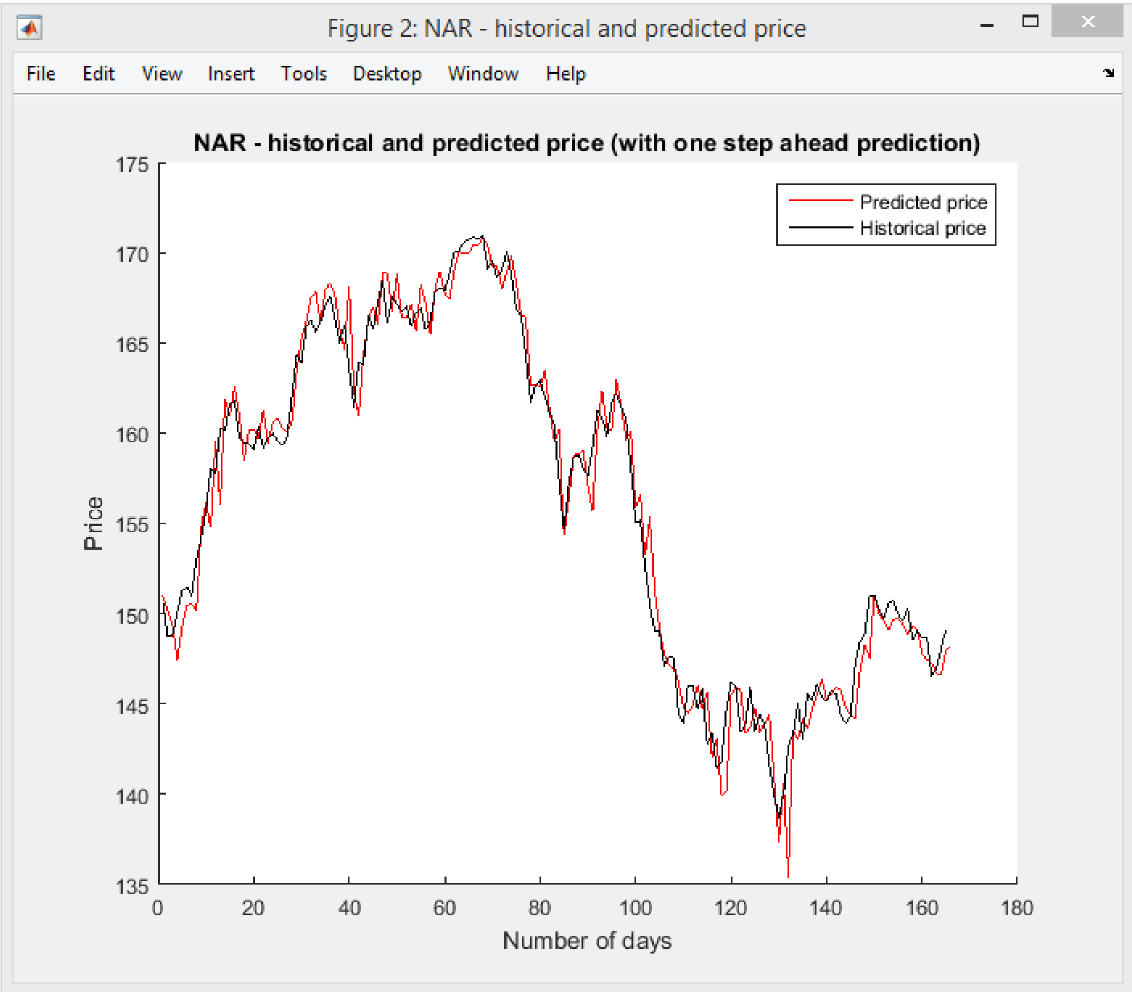

Figure 13: NAR Comparison of the predicted and historical price (Source: MATLAB R2015a)

The last plot related to the training of NAR neural network is displayed in **Figure 13**. It is very similar to **Figure 11**, it also shows comparison of the predicted values line and the line of historical values, with the difference that in Figure 8 the errors are not displayed, which makes it clearer in terms of the prediction of the trend. Also this figure adds the value of one step ahead prediction – the last point of the red line, which represents the predicted value.

The one step ahead prediction was achieved by removal of a delay from the network – from the tapped delay line. The output of the network is the $y(t+1)$ instead of $y(t)$. The scheme of the prediction model of the NAR network is shown in **Figure 14**. Compare it with the scheme of the training network in **Figure 7** (MathWorks, 2015).

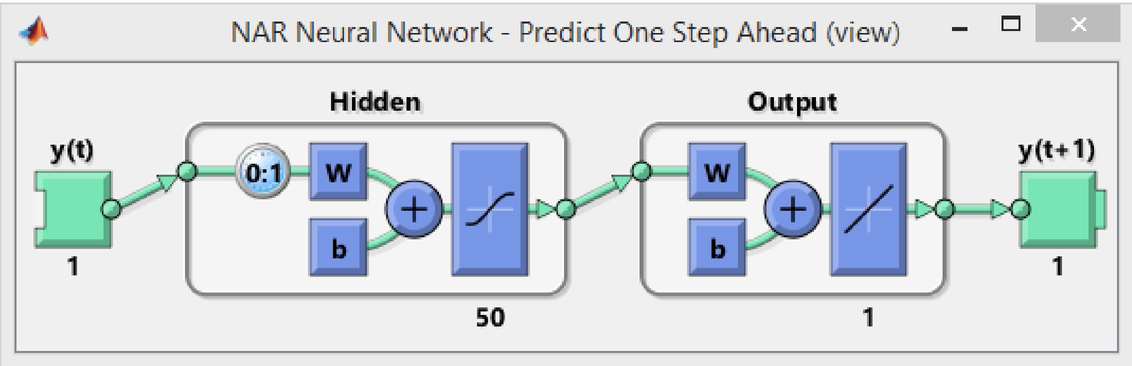

Figure 14: Diagram of the prediction NAR network (Source: MATLAB R2015a)

5.1.3 Results of the NAR network

This chapter focuses on the demonstration of the Live Cattle price prediction using the NAR neural network with one step ahead approach. As it was outlined in the 5.1 chapter, the date range used for training the network was 8 months (15/08/2014 – 15/04/2015). Then using the aforementioned one step ahead prediction, the close price of the next day was calculated. This predicted closing price is compared with the actual closing price of the previous day and based on that the trend is determined: ↑ **RISE** or ↓ **FALL**.

In order to somehow quantify the results of the network, an investment strategy is suggested here. Depending on the predicted trend, the user of the system would open a long or short position at the beginning of the next business day, therefore buying or selling for the open price, and then the position would be closed at the end of business day, hence selling or buying for the close price. The difference of the open price and close price, depending on the trend and kind of position the trader has chosen, would then represent the profit or loss that day. To put it into better perspective, **Table 2** below should make the suggested investment strategy clear.

Table 2: Summary of the potential investment strategy (Source: designed by the author)

Date	Real price Rp	Predicted price Pp	Condition C1	Predicted trend Pt	Condition C2	Position	Result
t-1	Rp(t-1)						
t	Rp(t)	Pp(t)	if Pp(t) > Rp(t-1) then	↑ RISE	if Pt = ↑ then	Long (BUY for OPEN, SELL for CLOSE)	Real CLOSE - Real OPEN
			if Pp(t) < Rp(t-1) then	↓ FALL	if Pt = ↓ then	Short (SELL for OPEN, BUY for CLOSE)	Real OPEN - Real CLOSE

Based on the strategy outlined in **Table 2**, and using the one step ahead prediction mention earlier, prices of the Live Cattle commodity were predicted for the next month following the end of the training data set. In order to simplify this demonstration no additional fees, as brokerage, etc., or leverage and margin related to futures trading, are taken into account. There were 4 different settings used for the NAR neural network, below are the results of those settings and the comparison of them.

The first setting of the NAR network is using 10 neurons in the hidden layer. The results are shown in **Table 3**.

Table 3: NAR network with 10 neurons in the hidden layer (Source: designed by the author)

NAR, Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	148,615	FALL	RISE	NO	1,186	-0,644
17.4.2015	149,902	146,853	149,713	FALL	FALL	YES	-2,860	3,050
20.4.2015	146,453	144,568	147,385	RISE	FALL	NO	-2,817	-1,885
21.4.2015	144,531	145,823	144,855	RISE	RISE	YES	0,968	1,291
22.4.2015	145,735	145,227	145,883	RISE	FALL	NO	-0,656	-0,508
23.4.2015	145,490	148,212	145,082	FALL	RISE	NO	3,129	-2,721
24.4.2015	148,431	150,064	147,410	FALL	RISE	NO	2,654	-1,633
27.4.2015	148,118	148,816	151,268	RISE	FALL	NO	-2,452	0,698
28.4.2015	148,851	149,286	148,296	FALL	RISE	NO	0,991	-0,435
29.4.2015	149,673	149,594	148,877	FALL	RISE	NO	0,717	0,079
30.4.2015	149,718	148,608	149,249	FALL	FALL	YES	-0,641	1,110
1.5.2015	148,459	148,455	148,574	FALL	FALL	YES	-0,119	0,004
4.5.2015	148,701	149,770	148,421	FALL	RISE	NO	1,349	-1,069
5.5.2015	150,098	150,508	150,110	RISE	RISE	YES	0,398	0,410
6.5.2015	150,410	149,720	150,312	FALL	FALL	YES	-0,593	0,690
7.5.2015	149,615	149,133	149,295	FALL	FALL	YES	-0,162	0,482
8.5.2015	149,825	150,468	148,341	FALL	RISE	NO	2,127	-0,643
11.5.2015	150,685	149,342	150,999	RISE	FALL	NO	-1,657	-1,344
12.5.2015	149,437	150,249	148,965	FALL	RISE	NO	1,284	-0,812
13.5.2015	150,108	151,253	150,122	FALL	RISE	NO	1,132	-1,145
14.5.2015	151,856	152,640	151,033	FALL	RISE	NO	1,606	-0,784
15.5.2015	152,952	151,308	152,775	RISE	FALL	NO	-1,467	-1,644
						31,82%		-$7,45

It is quite obvious that this setting is not correct for the selected dataset. It is not capable of determining the upcoming price change and it has a very low trend prediction success rate of 31,82%. If the investment (trading) strategy described in **Table 2** was used in this situation, if the long/short positions were entered with the open price and closed with the close price on the same day, the trader would **lose $7,45.** Therefore 10 neurons were not a good option for the NAR network, which didn't fit the time series well, and thus cannot be recommended.

Table 4: NAR network with 20 neurons in the hidden layer (Source: designed by the author)

NAR, Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,187	RISE	RISE	YES	0,614	0,644
17.4.2015	149,902	146,853	150,077	RISE	FALL	NO	-3,224	-3,050
20.4.2015	146,453	144,568	146,465	FALL	FALL	YES	-1,898	1,885
21.4.2015	144,531	145,823	146,831	RISE	RISE	YES	-1,009	1,291
22.4.2015	145,735	145,227	145,272	FALL	FALL	YES	-0,044	0,508
23.4.2015	145,490	148,212	145,128	FALL	RISE	NO	3,084	-2,721
24.4.2015	148,431	150,064	149,680	RISE	RISE	YES	0,384	1,633
27.4.2015	148,118	148,816	150,128	RISE	FALL	NO	-1,312	0,698
28.4.2015	148,851	149,286	148,660	FALL	RISE	NO	0,626	-0,435
29.4.2015	149,673	149,594	149,274	FALL	RISE	NO	0,321	0,079
30.4.2015	149,718	148,608	149,431	FALL	FALL	YES	-0,823	1,110
1.5.2015	148,459	148,455	148,102	FALL	FALL	YES	0,353	0,004
4.5.2015	148,701	149,770	148,973	RISE	RISE	YES	0,797	1,069
5.5.2015	150,098	150,508	150,155	RISE	RISE	YES	0,353	0,410
6.5.2015	150,410	149,720	150,396	FALL	FALL	YES	-0,676	0,690
7.5.2015	149,615	149,133	149,870	RISE	FALL	NO	-0,737	-0,482
8.5.2015	149,825	150,468	149,332	RISE	RISE	YES	1,136	0,643
11.5.2015	150,685	149,342	149,067	FALL	FALL	YES	0,275	1,344
12.5.2015	149,437	150,249	148,771	FALL	RISE	NO	1,477	-0,812
13.5.2015	150,108	151,253	149,692	FALL	RISE	NO	1,562	-1,145
14.5.2015	151,856	152,640	150,855	FALL	RISE	NO	1,785	-0,784
15.5.2015	152,952	151,308	153,303	RISE	FALL	NO	-1,994	-1,644
						54,55%		$0,94

When looking at the second NAR network in **Table 4**, which is using 20 neurons in the hidden layer, it is obvious the situation is much better than in case of the network with 10 neurons. In this case the strategy is actually a bit profitable – the final balance at the end of the month is for this network **$0,94 profit**. The success rate increased as well, to the value of 54,55%, so a bit more than half of the trends was predicted correctly. In spite of the profit, it is still a result that would not make much money for the trader.

Table 5: NAR network with 50 neurons in the hidden layer (Source: designed by the author)

NAR, Neurons: 50								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	150,135	RISE	RISE	YES	-0,334	0,644
17.4.2015	149,902	146,853	149,732	FALL	FALL	YES	-2,879	3,050
20.4.2015	146,453	144,568	147,073	RISE	FALL	NO	-2,505	-1,885
21.4.2015	144,531	145,823	146,084	RISE	RISE	YES	-0,261	1,291
22.4.2015	145,735	145,227	143,820	FALL	FALL	YES	1,408	0,508
23.4.2015	145,490	148,212	143,901	FALL	RISE	NO	4,310	-2,721
24.4.2015	148,431	150,064	150,643	RISE	RISE	YES	-0,579	1,633
27.4.2015	148,118	148,816	151,551	RISE	FALL	NO	-2,735	0,698
28.4.2015	148,851	149,286	148,569	FALL	RISE	NO	0,717	-0,435
29.4.2015	149,673	149,594	148,133	FALL	RISE	NO	1,461	0,079
30.4.2015	149,718	148,608	149,816	RISE	FALL	NO	-1,208	-1,110
1.5.2015	148,459	148,455	148,472	FALL	FALL	YES	-0,017	0,004
4.5.2015	148,701	149,770	148,869	RISE	RISE	YES	0,901	1,069
5.5.2015	150,098	150,508	149,669	FALL	RISE	NO	0,839	-0,410
6.5.2015	150,410	149,720	149,608	FALL	FALL	YES	0,111	0,690
7.5.2015	149,615	149,133	147,817	FALL	FALL	YES	1,316	0,482
8.5.2015	149,825	150,468	149,040	FALL	RISE	NO	1,428	-0,643
11.5.2015	150,685	149,342	149,914	FALL	FALL	YES	-0,572	1,344
12.5.2015	149,437	150,249	149,537	RISE	RISE	YES	0,712	0,812
13.5.2015	150,108	151,253	149,324	FALL	RISE	NO	1,929	-1,145
14.5.2015	151,856	152,640	150,389	FALL	RISE	NO	2,251	-0,784
15.5.2015	152,952	151,308	150,537	FALL	FALL	YES	0,771	1,644
						54,55%		**$4,81**

The third setting for the NAR neural network is using 50 neurons in the hidden layer and proves to be even better than the profitable one with 20 neurons. It is partly due to the fact that it was able to predict the trend correctly for a day with the highest price movement between the open price and the close price – this was on 17 April 2015, when the price of Live Cattle dropped from open price of $149,902 to the close price of $146,853. As you can see in **Table 5**, the neural network correctly predicted decreasing trend (FALL of the price), it was determined to enter a short position and thanks to that a profit of $3,05 could be made. Success rate of the trend prediction is the same as in the network with 20 neurons in the hidden layer – 54,55%.

Table 6: NAR network with 50 neurons in the hidden layer (Source: designed by the author)

NAR, Neurons: 100								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,780	RISE	RISE	YES	0,021	0,644
17.4.2015	149,902	146,853	148,241	FALL	FALL	YES	-1,388	3,050
20.4.2015	146,453	144,568	146,830	FALL	FALL	YES	-2,262	1,885
21.4.2015	144,531	145,823	140,229	FALL	RISE	NO	5,593	-1,291
22.4.2015	145,735	145,227	143,891	FALL	FALL	YES	1,336	0,508
23.4.2015	145,490	148,212	145,325	RISE	RISE	YES	2,886	2,721
24.4.2015	148,431	150,064	150,593	RISE	RISE	YES	-0,529	1,633
27.4.2015	148,118	148,816	151,693	RISE	FALL	NO	-2,876	0,698
28.4.2015	148,851	149,286	147,509	FALL	RISE	NO	1,777	-0,435
29.4.2015	149,673	149,594	148,712	FALL	RISE	NO	0,883	0,079
30.4.2015	149,718	148,608	148,700	FALL	FALL	YES	-0,091	1,110
1.5.2015	148,459	148,455	149,400	RISE	FALL	NO	-0,945	-0,004
4.5.2015	148,701	149,770	149,552	RISE	RISE	YES	0,218	1,069
5.5.2015	150,098	150,508	147,908	FALL	RISE	NO	2,600	-0,410
6.5.2015	150,410	149,720	150,150	FALL	FALL	YES	-0,430	0,690
7.5.2015	149,615	149,133	150,635	RISE	FALL	NO	-1,502	-0,482
8.5.2015	149,825	150,468	148,895	FALL	RISE	NO	1,574	-0,643
11.5.2015	150,685	149,342	151,031	RISE	FALL	NO	-1,689	-1,344
12.5.2015	149,437	150,249	149,154	FALL	RISE	NO	1,094	-0,812
13.5.2015	150,108	151,253	148,682	FALL	RISE	NO	2,571	-1,145
14.5.2015	151,856	152,640	152,057	RISE	RISE	YES	0,583	0,784
15.5.2015	152,952	151,308	146,945	FALL	FALL	YES	4,363	1,644
						50,00%		**$9,95**

The last case of the NAR neural network is using 100 neurons in the hidden layer. Results of this setting is shown in **Table 6**. As you can see, this is so far the most profitable option in spite of the low success rate of 50%. It means that only a half of the trend prediction was correct. The profit of $9,95 that would be earned on 15 May 2015, if the investment strategy was followed, is achieved thanks to the trend being predicted correctly on the right days, when the price movement was significant, e.g. 17 April, 20 April, 23 April, 15 May.

There are even some days when the trend is not predicted correctly, but a profit is noted down – for example 27 April. This is happening due to the fact that the open price is quite different from the close price of the previous day. So in the example of 27 April, the close price of the previous day was 150,064 and the real close price of 27 April 148,816. So the real trend is decreasing. But the predicted price for 27 April is 151,693 – so when compared to the close price of the previous day, the predicted trend is increasing, therefore a long position is suggested and entered. And because the open price of 27 April was 148,118, the long position actually turned profitable since it was closed at the end of the day at the price of 148,816.

5.2 NARX (Nonlinear Autoregressive with External/Exogenous) Input) network

This type of network is very similar to NAR network with the difference that besides past values of *y(t)* NARX is using another time series *x(t)*. In other words, NARX network is used to predict future values of a time series *y(t)* from past values of that time series and past values of a second time series *x(t)*. The NARX network can be described as follows:

$$y(t) = f(y(t-1), \ldots, y(t-n), x(t-1), \ldots, (t-n))$$

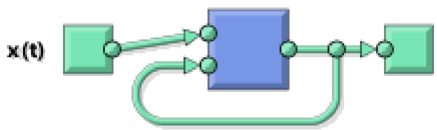

Figure 15: Diagram of general NARX network (Source: MATLAB R2015a)

Except for the external series of values used in the NARX network, it is the same as NAR network, so for detailed description of the process of using the network for prediction, refer to the 5.1 section of the thesis, which focuses on the NAR network.

5.2.1 Parameters of the NARX network

The parameters set for the NARX network are the same as the ones set for NAR network. For more details and definition of the individual parameters, refer to the 5.1.1 section. Follows a list of the used parameters and their values:

- **Number of delays**
  - Set to 2.
- **Number of hidden layer neurons**
  - This is the only parameter that is changing for individual run of the network in order to be compared later and decided which value provides the best and most accurate results. The values used: 10, 20, 50, 100.
- **Data division**
  - As well as with NAR network, the data are divided randomly using the *dividerand function.*
- **Training algorithm**
  - Levenberg-Marquardt (*trainlm*) is again the best fitting training algorithm for this problem.
- **Neural Network Performance Function**
  - Mean squared error (*mse*) is used as the performance function.

The only parameters that are used here and were not used in the NAR network are the technical indicators forming the external input $x(t)$.

5.2.2 Run of the NARX neural network

This chapter is focused on the run of the NARX network itself with the description of the individual steps leading to a successful training of the network and as accurate performance as possible. If any of the steps described below does not give you enough detail of the matter, refer to the 5.1.2 section, which focuses on the run of the NAR network. In order not to repeat the same, or very similar, procedures, this section might not be comprehensive enough if read without going through the previous chapters first.

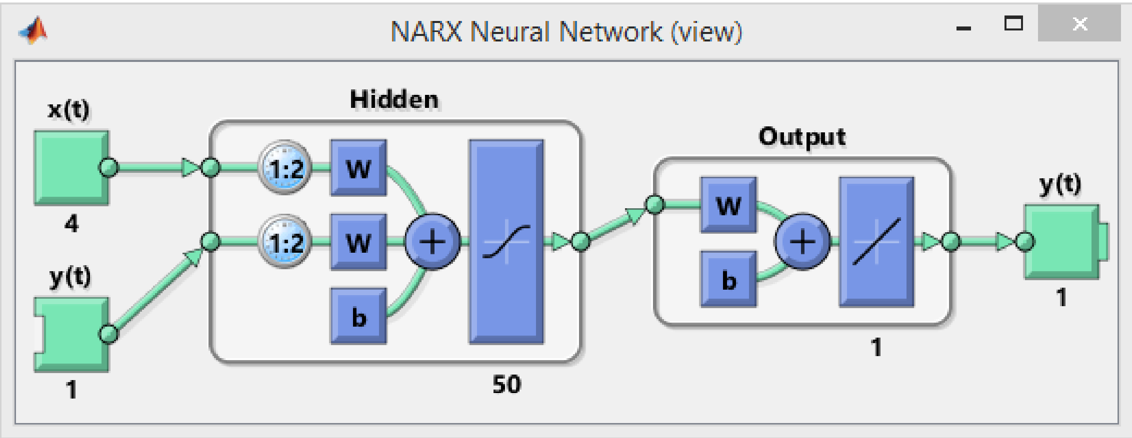

Figure 16: Diagram of the NARX network (Source: MATLAB R2015a)

As you can see in **Figure 16**, the delay is set to 2 for both inputs – the external input and the feedback connection from the network output. 50 neurons are used in the hidden layer. In the external input *x(t)* you can see that 4 time series were used to form the external input – those are the Open, High, Low prices and the RSI indicator with the period of 14. When the "NARX_Network.m" file containing the code is run in MATLAB, the following nonlinear autoregressive network with external (exogenous) input is created.

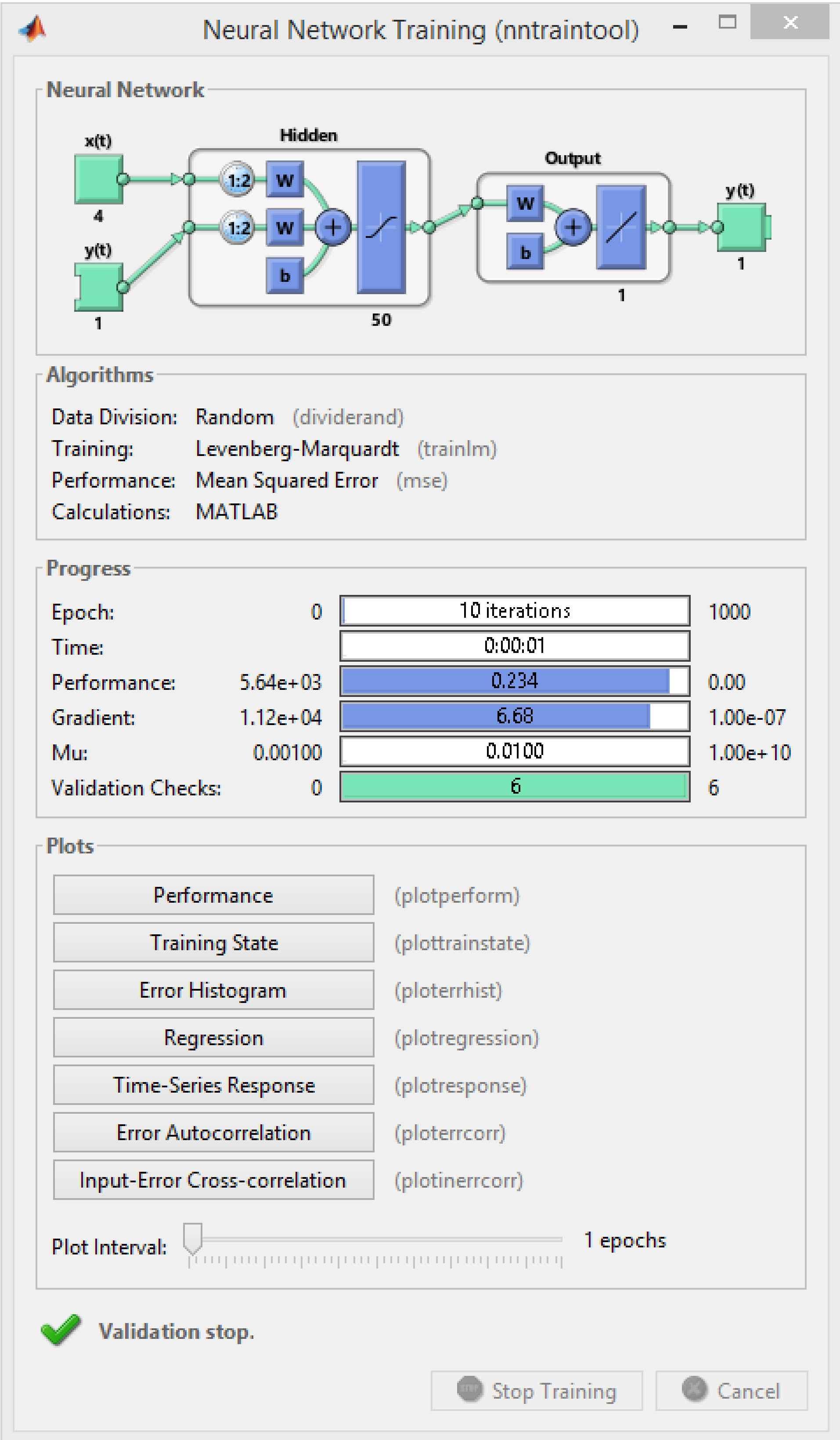

Figure 17: Training of the NARX network (Source: MATLAB R2015a)

The settings of the NARX network are obvious in **Figure 17**, 50 neurons used, delay set to 2, data divided randomly, Levenberg-Marquardt training algorithm used and Mean Squared Error selected as the performance function. According to the training results, the training continued until the validation error failed to decrease for 6 iterations (validation stop). Since total of 10 iterations was carried out, it is clear that the validation error stop decreasing in iteration 4.

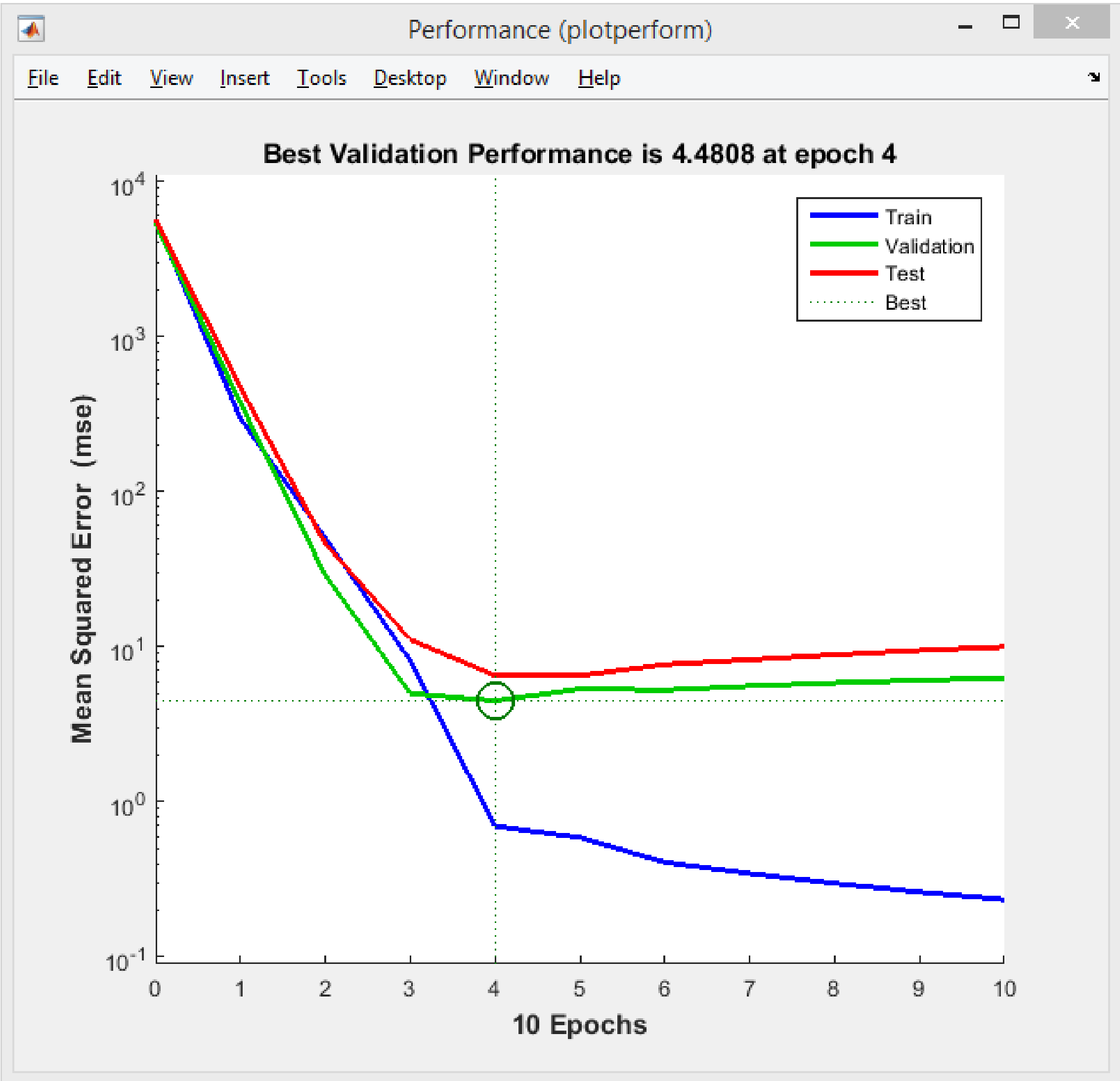

Figure 18: NARX Performance Training Record (Source: MATLAB R2015a)

The performance training record is plotted in **Figure 18** in order to check for potential overfitting of the network. The figure shows that the training, validation and testing errors all decreased until iteration 4, where the validation error reached its minimum of 4,4808. Since neither testing, nor validation increased before iteration 4, it does not seem that any overfitting has occurred (MathWorks, 2015).

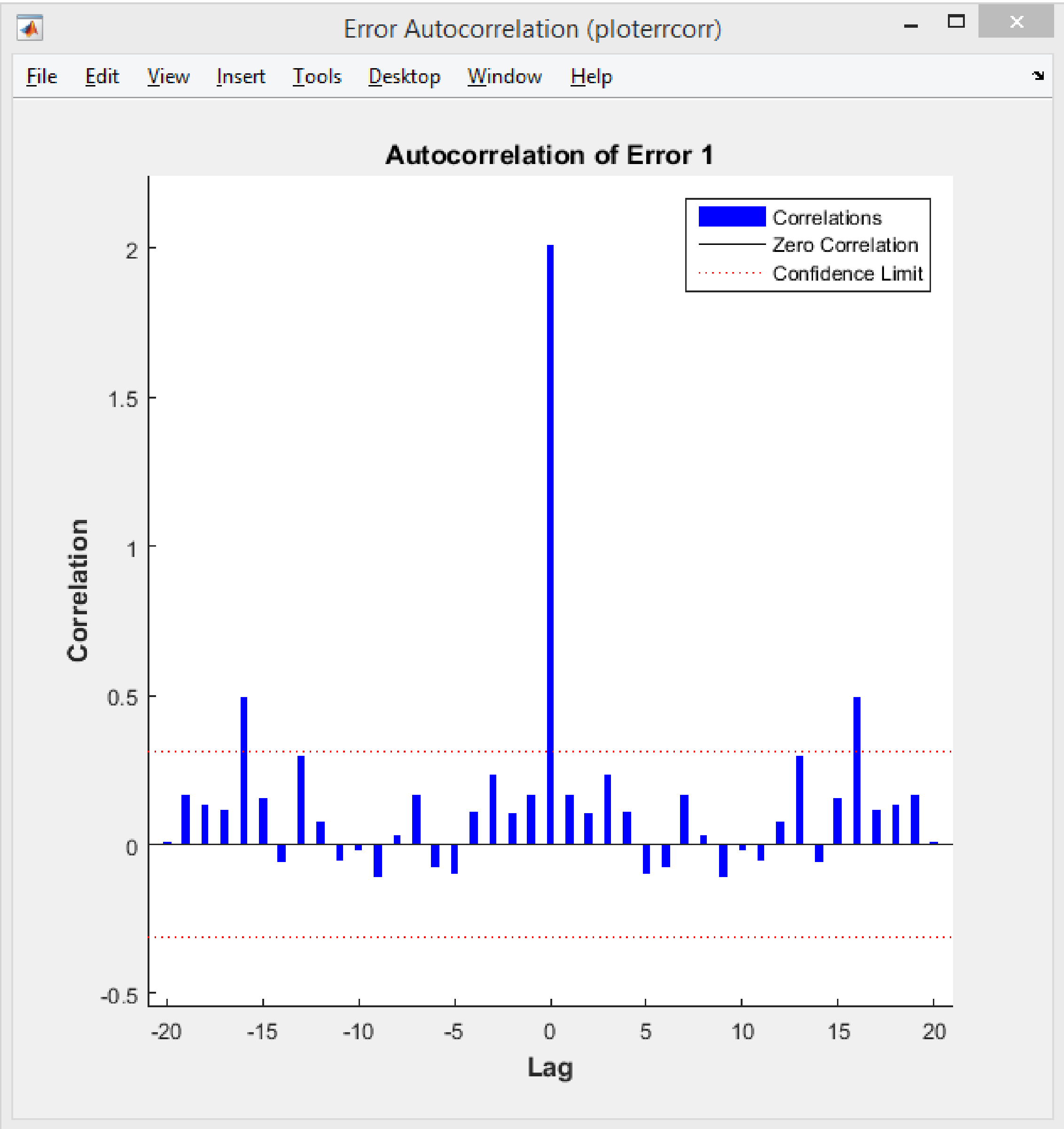

Figure 19: NARX Error Autocorrelation (Source: MATLAB R2015a)

As displayed in **Figure 19**, except for the one at zero lag, the correlations fall approximately within the 95% confidence limits around zero, so the model seems to be adequate. If there was significant correlation in the prediction errors, it should be possible to improve the prediction, for example by increasing the number of delays in the tapped delay line.

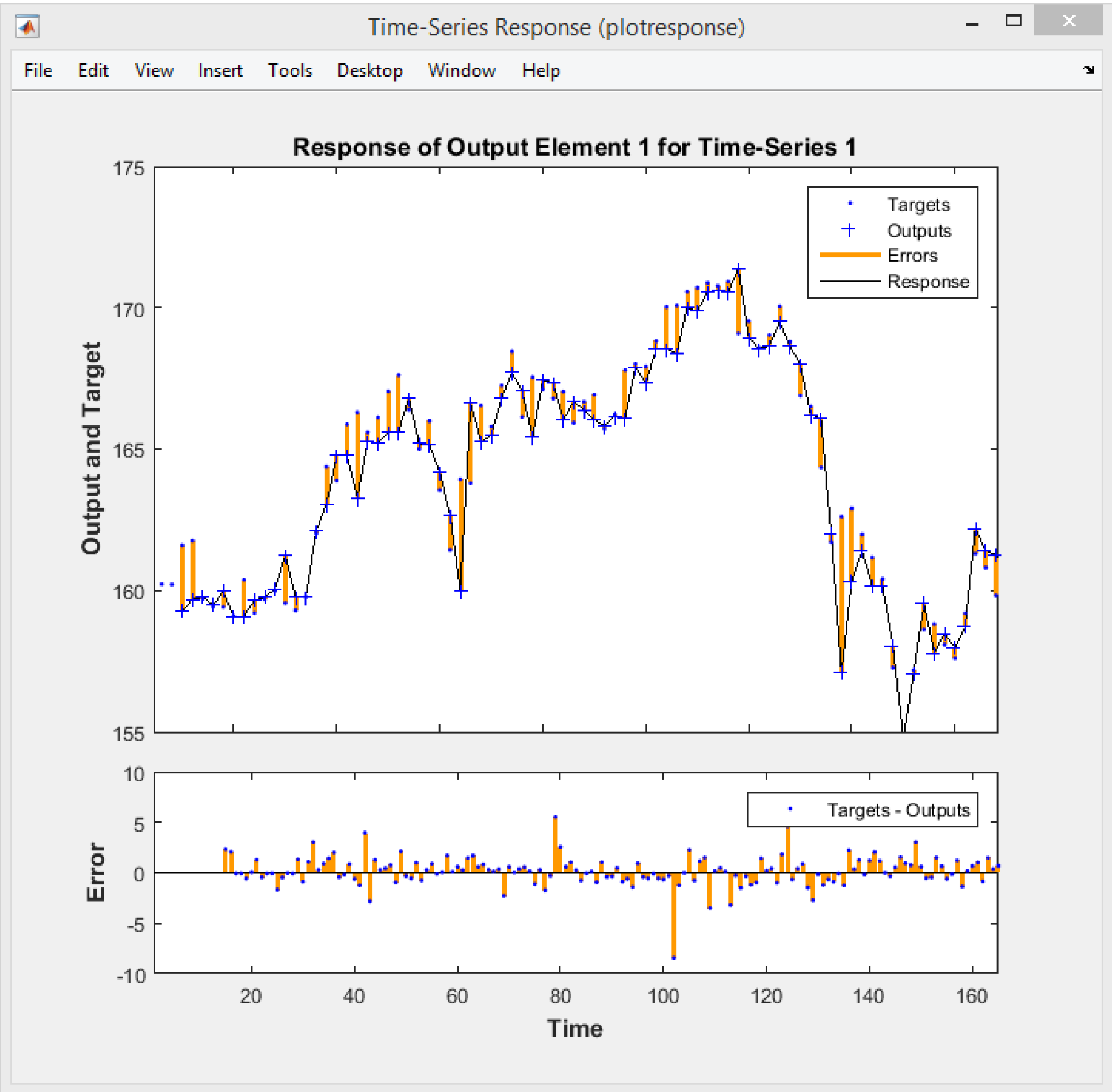

Figure 20: NARX Time-Series Response (Source: MATLAB R2015a)

The plot in **Figure 20** displays the targets, outputs and errors versus time. It is apparent that the training generated an output values that differ from the targets approximately by no more than around 2 in most cases. The plot is zoomed in, capturing just a portion of the whole plot in order to display the details better.

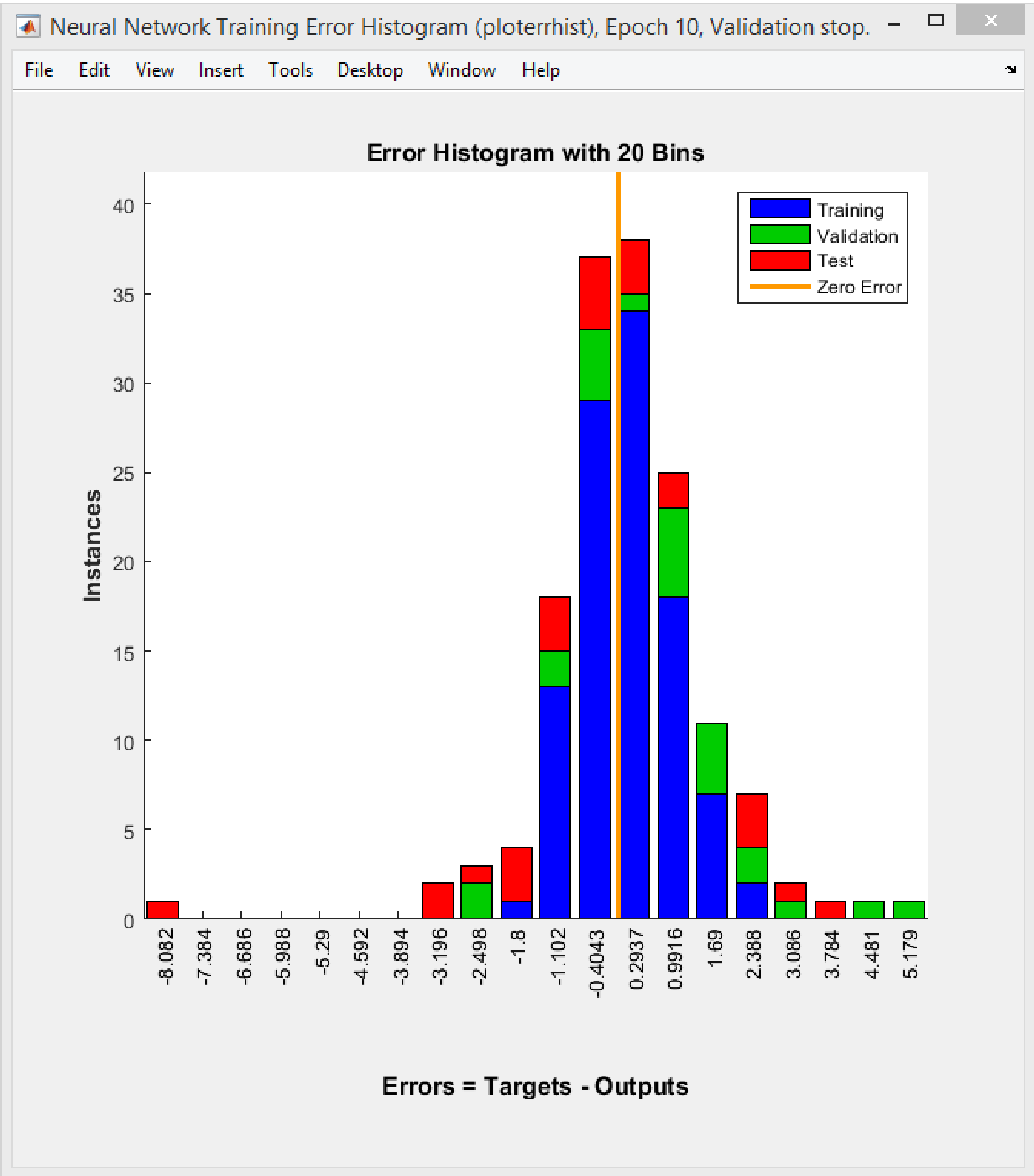

Figure 21: NARX Error Histogram (Source: MATLAB R2015a)

As the error histogram, displayed in **Figure 21**, shows, the errors are no very significant and most of them are present very close to zero, which would mean that the predicted values are very close to the target values.

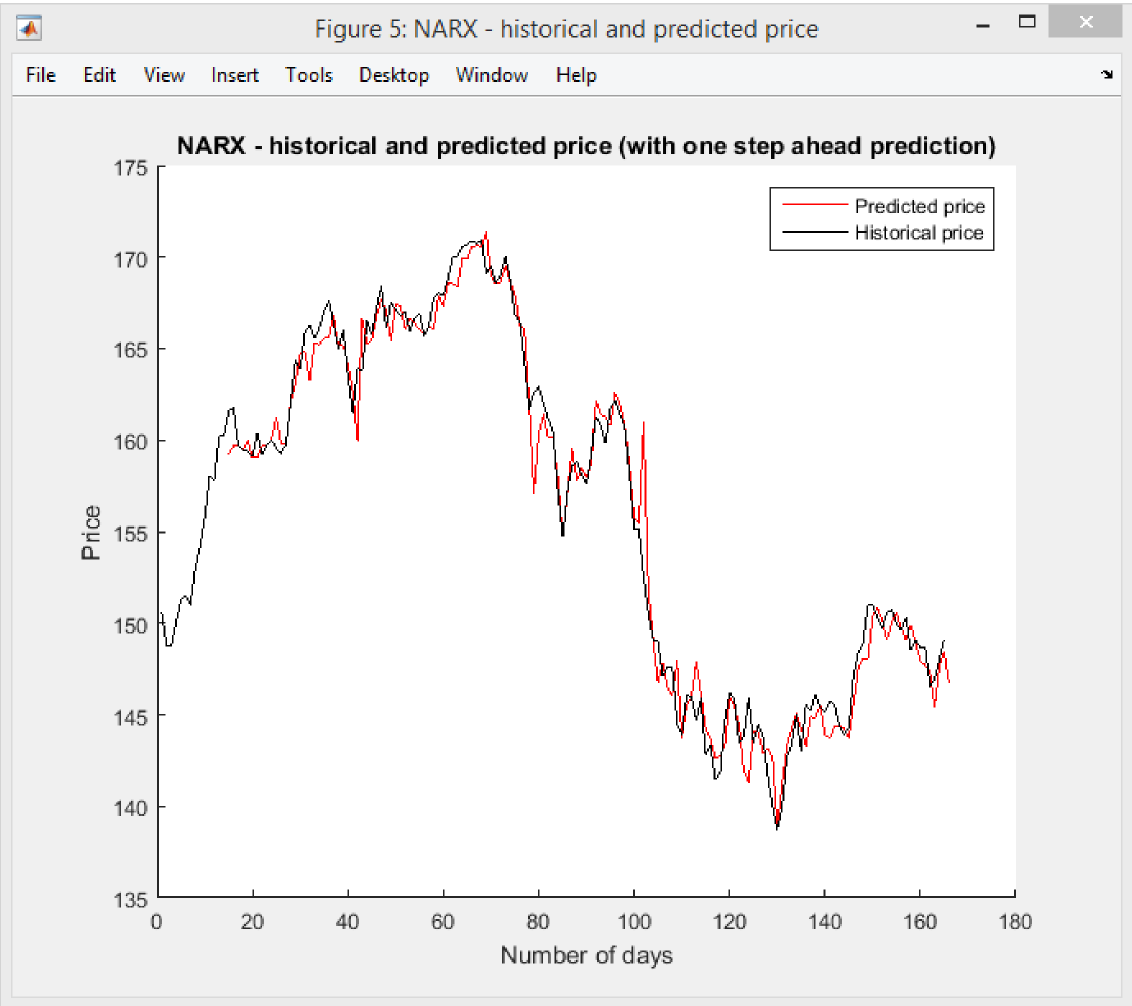

Figure 22: NARX Comparison of the predicted and historical price (Source: MATLAB R2015a)

The last plot related to the training of NARX neural network is displayed in **Figure 22**. It shows comparison of the predicted values line and the line of historical values. This figure also adds the one step ahead predicted value – the last point of the red line. It is visible in the plot that in about 102nd time step, the predicted value is far off the historical value – in order to see the size of the error, you can refer to **Figure 20** and see that the error in about 102nd time step is quite significant. This is an example how the individual diagrams can be examined in relation to each other.

The one step ahead prediction was achieved by removal of a delay from the network – from the tapped delay line. The output of the network is the *y(t+1)* instead of *y(t)*. The scheme of the prediction model of the NARX network is shown in **Figure 23**. Compare it with the scheme of the training network in **Figure 16** (MathWorks, 2015).

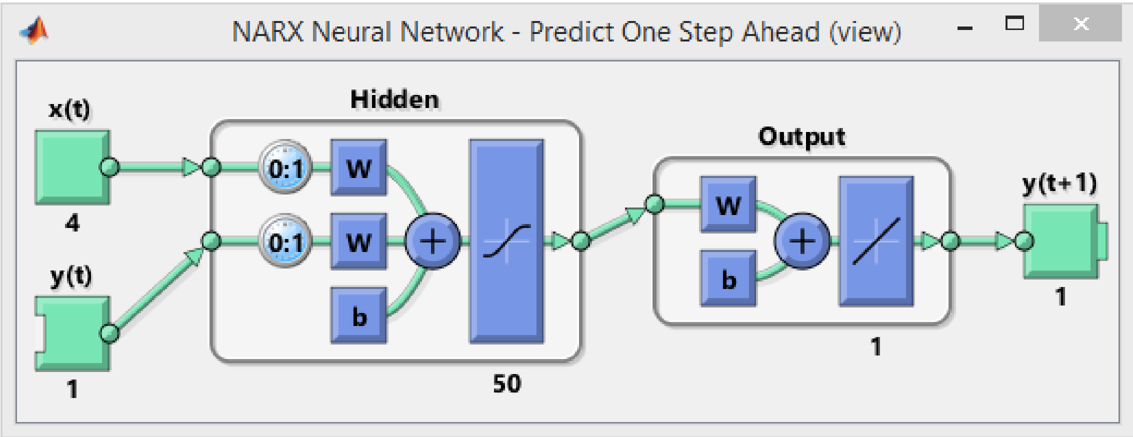

Figure 23: Diagram of the prediction NARX network (Source: MATLAB R2015a)

5.2.3 Results of the NARX network

This chapter focuses on the demonstration of the Live Cattle price prediction using the NARX neural network with one step ahead approach. As it was outlined in the 5.1 chapter for NAR, the date range used for training the network was 8 months (15/08/2014 – 15/04/2015). Then using the aforementioned one step ahead prediction, the close price of the next day was calculated. This predicted closing price is compared with the actual closing price of the previous day and based on that the trend is determined: ↑ **RISE** or ↓ **FALL**.

Refer to the 5.1.3 section and **Table 2** to understand the investment approach used within this chapter in order to somehow quantify the results. Following are the results of the NARX neural network predictions while using various technical indicators. Refer to the 3.3.2.1 section in the theoretical part of the thesis for the definition and detailed description of individual indicators used as external inputs in the NARX network.

Table 7: NARX network – 10 neurons, external: AD, OHL (Source: designed by the author)

NARX (AD,OHL), Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,574	RISE	RISE	YES	0,227	0,644
17.4.2015	149,902	146,853	147,250	FALL	FALL	YES	-0,397	3,050
20.4.2015	146,453	144,568	145,143	FALL	FALL	YES	-0,576	1,885
21.4.2015	144,531	145,823	148,256	RISE	RISE	YES	-2,433	1,291
22.4.2015	145,735	145,227	144,168	FALL	FALL	YES	1,060	0,508
23.4.2015	145,490	148,212	150,572	RISE	RISE	YES	-2,361	2,721
24.4.2015	148,431	150,064	151,267	RISE	RISE	YES	-1,204	1,633
27.4.2015	148,118	148,816	149,006	FALL	FALL	YES	-0,190	-0,698
28.4.2015	148,851	149,286	149,272	RISE	RISE	YES	0,015	0,435
29.4.2015	149,673	149,594	149,086	FALL	RISE	NO	0,508	0,079
30.4.2015	149,718	148,608	149,158	FALL	FALL	YES	-0,550	1,110
1.5.2015	148,459	148,455	148,486	FALL	FALL	YES	-0,031	0,004
4.5.2015	148,701	149,770	149,035	RISE	RISE	YES	0,735	1,069
5.5.2015	150,098	150,508	150,809	RISE	RISE	YES	-0,301	0,410
6.5.2015	150,410	149,720	149,765	FALL	FALL	YES	-0,045	0,690
7.5.2015	149,615	149,133	148,869	FALL	FALL	YES	0,264	0,482
8.5.2015	149,825	150,468	150,145	RISE	RISE	YES	0,323	0,643
11.5.2015	150,685	149,342	148,941	FALL	FALL	YES	0,401	1,344
12.5.2015	149,437	150,249	150,596	RISE	RISE	YES	-0,347	0,812
13.5.2015	150,108	151,253	150,755	RISE	RISE	YES	0,498	1,145
14.5.2015	151,856	152,640	152,888	RISE	RISE	YES	-0,248	0,784
15.5.2015	152,952	151,308	151,326	FALL	FALL	YES	-0,018	1,644
						95,45%		$21,69

In **Table 7** there are results of the NARX network using 10 neurons in the hidden layer and AD (Accumulation/distribution) line with OHL (Open, High, Low price) time series as the external input. This network performed well above expectations. While in NAR network, using 10 neurons in the hidden layer proved highly inefficient with success rate of only 31,82% and resulting loss of $7,45 in the potential trades, based on the trading strategy presented earlier. In this network the setting of 10 neuron together with AD and OHL as external input helped to the **success rate of 95,45%** and potential **profit of $21,69**. These are excellent results as the model predicted the upcoming trend incorrectly only once in 22 instances (number of business days within the month of prediction.

Table 8: NARX network – 20 neurons, external: AD, OHL (Source: designed by the author)

NARX (AD,OHL), Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	150,083	RISE	RISE	YES	-0,282	0,644
17.4.2015	149,902	146,853	148,078	FALL	FALL	YES	-1,226	3,050
20.4.2015	146,453	144,568	146,937	RISE	FALL	NO	-2,369	-1,885
21.4.2015	144,531	145,823	148,837	RISE	RISE	YES	-3,015	1,291
22.4.2015	145,735	145,227	146,160	RISE	FALL	NO	-0,932	-0,508
23.4.2015	145,490	148,212	149,958	RISE	RISE	YES	-1,746	2,721
24.4.2015	148,431	150,064	150,520	RISE	RISE	YES	-0,456	1,633
27.4.2015	148,118	148,816	149,009	FALL	FALL	YES	-0,193	-0,698
28.4.2015	148,851	149,286	148,114	FALL	RISE	NO	1,172	-0,435
29.4.2015	149,673	149,594	148,315	FALL	RISE	NO	1,279	0,079
30.4.2015	149,718	148,608	148,094	FALL	FALL	YES	0,514	1,110
1.5.2015	148,459	148,455	151,068	RISE	FALL	NO	-2,613	-0,004
4.5.2015	148,701	149,770	150,186	RISE	RISE	YES	-0,416	1,069
5.5.2015	150,098	150,508	149,917	RISE	RISE	YES	0,591	0,410
6.5.2015	150,410	149,720	147,908	FALL	FALL	YES	1,812	0,690
7.5.2015	149,615	149,133	149,729	RISE	FALL	NO	-0,596	-0,482
8.5.2015	149,825	150,468	150,982	RISE	RISE	YES	-0,514	0,643
11.5.2015	150,685	149,342	149,565	FALL	FALL	YES	-0,223	1,344
12.5.2015	149,437	150,249	151,992	RISE	RISE	YES	-1,743	0,812
13.5.2015	150,108	151,253	151,771	RISE	RISE	YES	-0,518	1,145
14.5.2015	151,856	152,640	153,981	RISE	RISE	YES	-1,342	0,784
15.5.2015	152,952	151,308	151,572	FALL	FALL	YES	-0,264	1,644
						72,73%		**$15,05**

Using 20 neurons in the NARX network with AD line and OHL series, as displayed in **Table 8**, performs a bit worse than the model with 10 neurons, but with 72,73% success rate and $15,05 profit still proves to be a reliable model and certainly more successful than the NAR models.

Table 9: NARX network – 50 neurons, external: AD, OHL (Source: designed by the author)

NARX (AD,OHL), Neurons: 50								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,844	RISE	RISE	YES	-0,043	0,644
17.4.2015	149,902	146,853	147,986	FALL	FALL	YES	-1,133	3,050
20.4.2015	146,453	144,568	147,863	RISE	FALL	NO	-3,295	-1,885
21.4.2015	144,531	145,823	147,123	RISE	RISE	YES	-1,300	1,291
22.4.2015	145,735	145,227	144,740	FALL	FALL	YES	0,487	0,508
23.4.2015	145,490	148,212	152,385	RISE	RISE	YES	-4,173	2,721
24.4.2015	148,431	150,064	150,358	RISE	RISE	YES	-0,294	1,633
27.4.2015	148,118	148,816	144,489	FALL	FALL	YES	4,327	-0,698
28.4.2015	148,851	149,286	143,086	FALL	RISE	NO	6,201	-0,435
29.4.2015	149,673	149,594	145,576	FALL	RISE	NO	4,018	0,079
30.4.2015	149,718	148,608	145,666	FALL	FALL	YES	2,942	1,110
1.5.2015	148,459	148,455	149,963	RISE	FALL	NO	-1,508	-0,004
4.5.2015	148,701	149,770	149,864	RISE	RISE	YES	-0,094	1,069
5.5.2015	150,098	150,508	150,417	RISE	RISE	YES	0,091	0,410
6.5.2015	150,410	149,720	151,064	RISE	FALL	NO	-1,344	-0,690
7.5.2015	149,615	149,133	149,158	FALL	FALL	YES	-0,025	0,482
8.5.2015	149,825	150,468	151,072	RISE	RISE	YES	-0,604	0,643
11.5.2015	150,685	149,342	150,620	RISE	FALL	NO	-1,278	-1,344
12.5.2015	149,437	150,249	150,561	RISE	RISE	YES	-0,312	0,812
13.5.2015	150,108	151,253	151,748	RISE	RISE	YES	-0,495	1,145
14.5.2015	151,856	152,640	155,801	RISE	RISE	YES	-3,161	0,784
15.5.2015	152,952	151,308	150,110	FALL	FALL	YES	1,198	1,644
						72,73%		**$12,97**

The NARX neural network with 50 neurons and AD line and OHL as external inputs performs very similarly to the one with 20 neurons. As apparent in **Table 9**, the success rate is the same 72,73%, the profit differs because the days for which the trend was predicted are different.

Table 10: NARX network – 100 neurons, external: AD, OHL (Source: designed by the author)

NARX (AD,OHL), Neurons: 100								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	148,331	FALL	RISE	NO	1,470	-0,644
17.4.2015	149,902	146,853	148,340	FALL	FALL	YES	-1,488	3,050
20.4.2015	146,453	144,568	141,329	FALL	FALL	YES	3,239	1,885
21.4.2015	144,531	145,823	147,792	RISE	RISE	YES	-1,969	1,291
22.4.2015	145,735	145,227	152,759	RISE	FALL	NO	-7,531	-0,508
23.4.2015	145,490	148,212	146,261	RISE	RISE	YES	1,951	2,721
24.4.2015	148,431	150,064	148,998	RISE	RISE	YES	1,066	1,633
27.4.2015	148,118	148,816	147,221	FALL	FALL	YES	1,595	-0,698
28.4.2015	148,851	149,286	148,102	FALL	RISE	NO	1,184	-0,435
29.4.2015	149,673	149,594	144,131	FALL	RISE	NO	5,463	0,079
30.4.2015	149,718	148,608	144,113	FALL	FALL	YES	4,495	1,110
1.5.2015	148,459	148,455	149,774	RISE	FALL	NO	-1,319	-0,004
4.5.2015	148,701	149,770	150,766	RISE	RISE	YES	-0,996	1,069
5.5.2015	150,098	150,508	151,317	RISE	RISE	YES	-0,809	0,410
6.5.2015	150,410	149,720	149,388	FALL	FALL	YES	0,331	0,690
7.5.2015	149,615	149,133	151,762	RISE	FALL	NO	-2,629	-0,482
8.5.2015	149,825	150,468	152,622	RISE	RISE	YES	-2,154	0,643
11.5.2015	150,685	149,342	150,890	RISE	FALL	NO	-1,548	-1,344
12.5.2015	149,437	150,249	152,441	RISE	RISE	YES	-2,192	0,812
13.5.2015	150,108	151,253	151,067	RISE	RISE	YES	0,186	1,145
14.5.2015	151,856	152,640	149,998	FALL	RISE	NO	2,641	-0,784
15.5.2015	152,952	151,308	145,937	FALL	FALL	YES	5,371	1,644
						63,64%		**$13,28**

It seems that for the NARX network with AD and OHL as external inputs, the success rate decreases with the increasing number of neurons in the hidden layer. But even the results of the network with 100 neurons, displayed in **Table 10**, are not bad at all. Success rate of 63,64% and profit of $13,28 are still better than the results of NAR networks.

Table 11: NARX network – 10 neurons, external: RSI14, SMA10, EMA10, OHL (Source: designed by the author)

NARX (RSI14,SMA10,EMA10, OHL), Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,581	RISE	RISE	YES	0,220	0,644
17.4.2015	149,902	146,853	147,414	FALL	FALL	YES	-0,561	3,050
20.4.2015	146,453	144,568	144,067	FALL	FALL	YES	0,501	1,885
21.4.2015	144,531	145,823	145,020	RISE	RISE	YES	0,802	1,291
22.4.2015	145,735	145,227	144,373	FALL	FALL	YES	0,854	0,508
23.4.2015	145,490	148,212	146,095	RISE	RISE	YES	2,117	2,721
24.4.2015	148,431	150,064	151,691	RISE	RISE	YES	-1,627	1,633
27.4.2015	148,118	148,816	149,982	FALL	FALL	YES	-1,166	-0,698
28.4.2015	148,851	149,286	149,525	RISE	RISE	YES	-0,239	0,435
29.4.2015	149,673	149,594	148,695	FALL	RISE	NO	0,899	0,079
30.4.2015	149,718	148,608	147,154	FALL	FALL	YES	1,454	1,110
1.5.2015	148,459	148,455	146,550	FALL	FALL	YES	1,905	0,004
4.5.2015	148,701	149,770	149,374	RISE	RISE	YES	0,397	1,069
5.5.2015	150,098	150,508	149,597	FALL	RISE	NO	0,912	-0,410
6.5.2015	150,410	149,720	149,655	FALL	FALL	YES	0,064	0,690
7.5.2015	149,615	149,133	148,691	FALL	FALL	YES	0,442	0,482
8.5.2015	149,825	150,468	150,358	RISE	RISE	YES	0,111	0,643
11.5.2015	150,685	149,342	149,064	FALL	FALL	YES	0,278	1,344
12.5.2015	149,437	150,249	150,058	RISE	RISE	YES	0,191	0,812
13.5.2015	150,108	151,253	151,365	RISE	RISE	YES	-0,112	1,145
14.5.2015	151,856	152,640	151,813	RISE	RISE	YES	0,826	0,784
15.5.2015	152,952	151,308	149,592	FALL	FALL	YES	1,716	1,644
						90,91%		$20,86

In **Table 11** is displayed another very successful 10 neuron NARX network, this time with the following indicators: RSI14,SMA10,EMA10, OHL. This network was able to achieve outstanding results – **success rate 90,91%** and profit of **$20,86.**

Table 12: NARX network – 20 neurons, external: RSI14, SMA10, EMA10, OHL (Source: designed by the author)

NARX (RSI14,SMA10,EMA10, OHL), Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,204	RISE	RISE	YES	0,597	0,644
17.4.2015	149,902	146,853	147,414	FALL	FALL	YES	-0,561	3,050
20.4.2015	146,453	144,568	144,797	FALL	FALL	YES	-0,229	1,885
21.4.2015	144,531	145,823	144,563	FALL	RISE	NO	1,259	-1,291
22.4.2015	145,735	145,227	144,191	FALL	FALL	YES	1,036	0,508
23.4.2015	145,490	148,212	147,605	RISE	RISE	YES	0,607	2,721
24.4.2015	148,431	150,064	149,342	RISE	RISE	YES	0,721	1,633
27.4.2015	148,118	148,816	151,902	RISE	FALL	NO	-3,086	0,698
28.4.2015	148,851	149,286	147,525	FALL	RISE	NO	1,762	-0,435
29.4.2015	149,673	149,594	148,375	FALL	RISE	NO	1,219	0,079
30.4.2015	149,718	148,608	147,705	FALL	FALL	YES	0,903	1,110
1.5.2015	148,459	148,455	150,481	RISE	FALL	NO	-2,026	-0,004
4.5.2015	148,701	149,770	149,094	RISE	RISE	YES	0,676	1,069
5.5.2015	150,098	150,508	150,079	RISE	RISE	YES	0,429	0,410
6.5.2015	150,410	149,720	149,015	FALL	FALL	YES	0,705	0,690
7.5.2015	149,615	149,133	148,698	FALL	FALL	YES	0,435	0,482
8.5.2015	149,825	150,468	149,218	RISE	RISE	YES	1,251	0,643
11.5.2015	150,685	149,342	148,991	FALL	FALL	YES	0,351	1,344
12.5.2015	149,437	150,249	149,980	RISE	RISE	YES	0,269	0,812
13.5.2015	150,108	151,253	151,452	RISE	RISE	YES	-0,199	1,145
14.5.2015	151,856	152,640	153,753	RISE	RISE	YES	-1,113	0,784
15.5.2015	152,952	151,308	150,682	FALL	FALL	YES	0,626	1,644
						77,27%		**$19,62**

Table 13: NARX network – 50 neurons, external: RSI14, SMA10, EMA10, OHL (Source: designed by the author)

NARX (RSI14,SMA10,EMA10, OHL), Neurons: 50								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	150,437	RISE	RISE	YES	-0,636	0,644
17.4.2015	149,902	146,853	151,664	RISE	FALL	NO	-4,811	-3,050
20.4.2015	146,453	144,568	143,311	FALL	FALL	YES	1,257	1,885
21.4.2015	144,531	145,823	150,678	RISE	RISE	YES	-4,856	1,291
22.4.2015	145,735	145,227	142,861	FALL	FALL	YES	2,366	0,508
23.4.2015	145,490	148,212	144,723	FALL	RISE	NO	3,489	-2,721
24.4.2015	148,431	150,064	149,670	RISE	RISE	YES	0,393	1,633
27.4.2015	148,118	148,816	149,515	FALL	FALL	YES	-0,699	-0,698
28.4.2015	148,851	149,286	149,449	RISE	RISE	YES	-0,162	0,435
29.4.2015	149,673	149,594	149,574	RISE	RISE	YES	0,021	-0,079
30.4.2015	149,718	148,608	146,377	FALL	FALL	YES	2,231	1,110
1.5.2015	148,459	148,455	151,787	RISE	FALL	NO	-3,332	-0,004
4.5.2015	148,701	149,770	150,438	RISE	RISE	YES	-0,668	1,069
5.5.2015	150,098	150,508	149,556	FALL	RISE	NO	0,952	-0,410
6.5.2015	150,410	149,720	148,555	FALL	FALL	YES	1,165	0,690
7.5.2015	149,615	149,133	151,110	RISE	FALL	NO	-1,977	-0,482
8.5.2015	149,825	150,468	149,253	RISE	RISE	YES	1,215	0,643
11.5.2015	150,685	149,342	147,852	FALL	FALL	YES	1,490	1,344
12.5.2015	149,437	150,249	152,004	RISE	RISE	YES	-1,755	0,812
13.5.2015	150,108	151,253	150,597	RISE	RISE	YES	0,657	1,145
14.5.2015	151,856	152,640	155,261	RISE	RISE	YES	-2,621	0,784
15.5.2015	152,952	151,308	151,264	FALL	FALL	YES	0,045	1,644
						77,27%		**$8,19**

Model NARX with the external indicators (RSI14, SMA10, EMA10, OHL) and 50 neurons, displayed in **Table 13**, is a perfect example of the fact that success rate does not mean much, when the trend is not predicted on significant days. Profit of $8,19 is not bad, but when compared with the profit of the previous network with 20 neurons, which has the same success rate of 77,27%, but profit of $19,62, it suddenly does not seem as good as before.

Table 14: NARX network – 100 neurons, external: RSI14, SMA10, EMA10, OHL (Source: designed by the author)

NARX (RSI14,SMA10,EMA10, OHL), Neurons: 100								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	151,609	RISE	RISE	YES	-1,808	0,644
17.4.2015	149,902	146,853	150,356	RISE	FALL	NO	-3,503	-3,050
20.4.2015	146,453	144,568	146,360	FALL	FALL	YES	-1,792	1,885
21.4.2015	144,531	145,823	144,308	FALL	RISE	NO	1,515	-1,291
22.4.2015	145,735	145,227	145,601	FALL	FALL	YES	-0,373	0,508
23.4.2015	145,490	148,212	148,787	RISE	RISE	YES	-0,576	2,721
24.4.2015	148,431	150,064	152,691	RISE	RISE	YES	-2,627	1,633
27.4.2015	148,118	148,816	146,636	FALL	FALL	YES	2,180	-0,698
28.4.2015	148,851	149,286	148,143	FALL	RISE	NO	1,144	-0,435
29.4.2015	149,673	149,594	147,367	FALL	RISE	NO	2,227	0,079
30.4.2015	149,718	148,608	144,798	FALL	FALL	YES	3,810	1,110
1.5.2015	148,459	148,455	148,996	RISE	FALL	NO	-0,542	-0,004
4.5.2015	148,701	149,770	147,487	FALL	RISE	NO	2,283	-1,069
5.5.2015	150,098	150,508	148,141	FALL	RISE	NO	2,367	-0,410
6.5.2015	150,410	149,720	146,651	FALL	FALL	YES	3,069	0,690
7.5.2015	149,615	149,133	147,243	FALL	FALL	YES	1,890	0,482
8.5.2015	149,825	150,468	149,312	RISE	RISE	YES	1,156	0,643
11.5.2015	150,685	149,342	146,528	FALL	FALL	YES	2,814	1,344
12.5.2015	149,437	150,249	152,430	RISE	RISE	YES	-2,181	0,812
13.5.2015	150,108	151,253	150,034	FALL	RISE	NO	1,219	-1,145
14.5.2015	151,856	152,640	158,151	RISE	RISE	YES	-5,512	0,784
15.5.2015	152,952	151,308	148,854	FALL	FALL	YES	2,454	1,644
						63,64%		**$6,87**

As suggested with the NARX network with indicators AD,OHL, now it seems to be proven that the NARX network's success rate decreases with the increasing number of neurons in the hidden layer.

Table 15: NARX network – 10 neurons, external: RSI7, SMA5, ROC5, OHL (Source: designed by the author)

NARX (RSI7,SMA5,ROC5, OHL), Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	150,115	RISE	RISE	YES	-0,315	0,644
17.4.2015	149,902	146,853	147,454	FALL	FALL	YES	-0,601	3,050
20.4.2015	146,453	144,568	143,003	FALL	FALL	YES	1,565	1,885
21.4.2015	144,531	145,823	145,147	RISE	RISE	YES	0,676	1,291
22.4.2015	145,735	145,227	145,241	FALL	FALL	YES	-0,013	0,508
23.4.2015	145,490	148,212	150,676	RISE	RISE	YES	-2,464	2,721
24.4.2015	148,431	150,064	150,852	RISE	RISE	YES	-0,789	1,633
27.4.2015	148,118	148,816	150,078	RISE	FALL	NO	-1,262	0,698
28.4.2015	148,851	149,286	149,481	RISE	RISE	YES	-0,195	0,435
29.4.2015	149,673	149,594	150,278	RISE	RISE	YES	-0,684	-0,079
30.4.2015	149,718	148,608	147,323	FALL	FALL	YES	1,285	1,110
1.5.2015	148,459	148,455	147,817	FALL	FALL	YES	0,638	0,004
4.5.2015	148,701	149,770	149,078	RISE	RISE	YES	0,692	1,069
5.5.2015	150,098	150,508	149,863	RISE	RISE	YES	0,645	0,410
6.5.2015	150,410	149,720	149,040	FALL	FALL	YES	0,679	0,690
7.5.2015	149,615	149,133	149,315	FALL	FALL	YES	-0,182	0,482
8.5.2015	149,825	150,468	150,778	RISE	RISE	YES	-0,310	0,643
11.5.2015	150,685	149,342	149,063	FALL	FALL	YES	0,279	1,344
12.5.2015	149,437	150,249	150,793	RISE	RISE	YES	-0,544	0,812
13.5.2015	150,108	151,253	151,021	RISE	RISE	YES	0,232	1,145
14.5.2015	151,856	152,640	153,451	RISE	RISE	YES	-0,812	0,784
15.5.2015	152,952	151,308	151,847	FALL	FALL	YES	-0,539	1,644
						95,45%		$22,92

Table 16: NARX network – 20 neurons, external: RSI7, SMA5, ROC5, OHL (Source: designed by the author)

NARX (RSI7,SMA5,ROC5, OHL), Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,538	RISE	RISE	YES	0,263	0,644
17.4.2015	149,902	146,853	147,135	FALL	FALL	YES	-0,282	3,050
20.4.2015	146,453	144,568	144,033	FALL	FALL	YES	0,535	1,885
21.4.2015	144,531	145,823	146,965	RISE	RISE	YES	-1,143	1,291
22.4.2015	145,735	145,227	144,021	FALL	FALL	YES	1,206	0,508
23.4.2015	145,490	148,212	145,773	RISE	RISE	YES	2,439	2,721
24.4.2015	148,431	150,064	154,891	RISE	RISE	YES	-4,827	1,633
27.4.2015	148,118	148,816	148,855	FALL	FALL	YES	-0,038	-0,698
28.4.2015	148,851	149,286	150,611	RISE	RISE	YES	-1,324	0,435
29.4.2015	149,673	149,594	150,352	RISE	RISE	YES	-0,757	-0,079
30.4.2015	149,718	148,608	149,641	RISE	FALL	NO	-1,033	-1,110
1.5.2015	148,459	148,455	146,643	FALL	FALL	YES	1,812	0,004
4.5.2015	148,701	149,770	150,131	RISE	RISE	YES	-0,361	1,069
5.5.2015	150,098	150,508	147,339	FALL	RISE	NO	3,169	-0,410
6.5.2015	150,410	149,720	149,567	FALL	FALL	YES	0,152	0,690
7.5.2015	149,615	149,133	149,264	FALL	FALL	YES	-0,131	0,482
8.5.2015	149,825	150,468	150,590	RISE	RISE	YES	-0,122	0,643
11.5.2015	150,685	149,342	149,698	FALL	FALL	YES	-0,356	1,344
12.5.2015	149,437	150,249	150,309	RISE	RISE	YES	-0,060	0,812
13.5.2015	150,108	151,253	151,603	RISE	RISE	YES	-0,350	1,145
14.5.2015	151,856	152,640	153,248	RISE	RISE	YES	-0,608	0,784
15.5.2015	152,952	151,308	151,978	FALL	FALL	YES	-0,670	1,644
						90,91%		**$18,49**

Table 17: NARX network – 50 neurons, external: RSI7, SMA5, ROC5, OHL (Source: designed by the author)

NARX (RSI7,SMA5,ROC5, OHL), Neurons: 50								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	145,537	FALL	RISE	NO	4,264	-0,644
17.4.2015	149,902	146,853	147,021	FALL	FALL	YES	-0,168	3,050
20.4.2015	146,453	144,568	147,367	RISE	FALL	NO	-2,799	-1,885
21.4.2015	144,531	145,823	150,600	RISE	RISE	YES	-4,778	1,291
22.4.2015	145,735	145,227	144,900	FALL	FALL	YES	0,327	0,508
23.4.2015	145,490	148,212	151,764	RISE	RISE	YES	-3,552	2,721
24.4.2015	148,431	150,064	146,321	FALL	RISE	NO	3,743	-1,633
27.4.2015	148,118	148,816	148,304	FALL	FALL	YES	0,512	-0,698
28.4.2015	148,851	149,286	148,972	RISE	RISE	YES	0,314	0,435
29.4.2015	149,673	149,594	150,124	RISE	RISE	YES	-0,530	-0,079
30.4.2015	149,718	148,608	147,755	FALL	FALL	YES	0,853	1,110
1.5.2015	148,459	148,455	147,762	FALL	FALL	YES	0,693	0,004
4.5.2015	148,701	149,770	145,566	FALL	RISE	NO	4,204	-1,069
5.5.2015	150,098	150,508	150,382	RISE	RISE	YES	0,126	0,410
6.5.2015	150,410	149,720	149,593	FALL	FALL	YES	0,127	0,690
7.5.2015	149,615	149,133	149,844	RISE	FALL	NO	-0,711	-0,482
8.5.2015	149,825	150,468	148,760	FALL	RISE	NO	1,708	-0,643
11.5.2015	150,685	149,342	149,361	FALL	FALL	YES	-0,019	1,344
12.5.2015	149,437	150,249	152,741	RISE	RISE	YES	-2,492	0,812
13.5.2015	150,108	151,253	152,870	RISE	RISE	YES	-1,617	1,145
14.5.2015	151,856	152,640	153,077	RISE	RISE	YES	-0,437	0,784
15.5.2015	152,952	151,308	157,955	RISE	FALL	NO	-6,647	-1,644
						68,18%		$5,53

Table 18: NARX network – 100 neurons, external: RSI7, SMA5, ROC5, OHL (Source: designed by the author)

NARX (RSI7,SMA5,ROC5, OHL), Neurons: 100								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	148,386	FALL	RISE	NO	1,415	-0,644
17.4.2015	149,902	146,853	147,055	FALL	FALL	YES	-0,202	3,050
20.4.2015	146,453	144,568	144,890	FALL	FALL	YES	-0,322	1,885
21.4.2015	144,531	145,823	146,809	RISE	RISE	YES	-0,986	1,291
22.4.2015	145,735	145,227	146,376	RISE	FALL	NO	-1,149	-0,508
23.4.2015	145,490	148,212	142,473	FALL	RISE	NO	5,739	-2,721
24.4.2015	148,431	150,064	150,177	RISE	RISE	YES	-0,113	1,633
27.4.2015	148,118	148,816	146,923	FALL	FALL	YES	1,893	-0,698
28.4.2015	148,851	149,286	143,850	FALL	RISE	NO	5,436	-0,435
29.4.2015	149,673	149,594	146,801	FALL	RISE	NO	2,793	0,079
30.4.2015	149,718	148,608	149,979	RISE	FALL	NO	-1,371	-1,110
1.5.2015	148,459	148,455	146,823	FALL	FALL	YES	1,632	0,004
4.5.2015	148,701	149,770	145,882	FALL	RISE	NO	3,888	-1,069
5.5.2015	150,098	150,508	148,726	FALL	RISE	NO	1,782	-0,410
6.5.2015	150,410	149,720	149,773	FALL	FALL	YES	-0,053	0,690
7.5.2015	149,615	149,133	148,904	FALL	FALL	YES	0,230	0,482
8.5.2015	149,825	150,468	148,630	FALL	RISE	NO	1,838	-0,643
11.5.2015	150,685	149,342	148,000	FALL	FALL	YES	1,342	1,344
12.5.2015	149,437	150,249	150,369	RISE	RISE	YES	-0,120	0,812
13.5.2015	150,108	151,253	153,301	RISE	RISE	YES	-2,048	1,145
14.5.2015	151,856	152,640	154,940	RISE	RISE	YES	-2,300	0,784
15.5.2015	152,952	151,308	150,739	FALL	FALL	YES	0,569	1,644
						59,09%		$6,60

This last series of the NARX networks (Table 15-18) proved the initial assumption that a NARX network with fewer neurons in the hidden layer is more efficient than a network with higher number of neurons when it comes to adding external inputs, represented by various technical indicators, to the network.

5.3 Summary of results of NAR and NARX networks

This chapter focuses on summarizing the results of the training and prediction of the NAR and NARX neural networks. It has been proved that more accurate and successful are NARX networks, where various technical indicators are used as the external inputs. In **Table 19** below it is easily recognizable which networks, using which parameters, were the most successful. As the best option seems the use of technical indicators with short period, together with small number of neurons – the NARX network with 10 or 20 neurons in the hidden layer and with the following indicators used as external input: RSI7, SMA5, ROC5 (plus the OHL). Success rate 95,45% and 90,91%, profit $22,92, $18,49 using 10 and 20 neurons, respectively. The detailed tables for the last six NARX networks in **Table 19** are attached at the end of the thesis.

Table 19: Summary of all tested NAR and NARX networks (Source: designed by the author)

Neural Network model	Success Rate	Open vs Close difference
NAR, Neurons: 10	31,82%	-$7,45
NAR, Neurons: 20	54,55%	$0,94
NAR, Neurons: 50	54,55%	$4,81
NAR, Neurons: 100	50,00%	$9,95
NARX (AD,OHL), Neurons: 10	95,45%	$21,69
NARX (AD,OHL), Neurons: 20	72,73%	$15,05
NARX (AD,OHL), Neurons: 50	72,73%	$12,97
NARX (AD,OHL), Neurons: 100	63,64%	$13,28
NARX (RSI14,SMA10,EMA10, OHL), Neurons: 10	90,91%	$20,86
NARX (RSI14,SMA10,EMA10, OHL), Neurons: 20	77,27%	$19,62
NARX (RSI14,SMA10,EMA10, OHL), Neurons: 50	77,27%	$8,19
NARX (RSI14,SMA10,EMA10, OHL), Neurons: 100	63,64%	$6,87
NARX (RSI7,SMA5,ROC5, OHL), Neurons: 10	95,45%	$22,92
NARX (RSI7,SMA5,ROC5, OHL), Neurons: 20	90,91%	$18,49
NARX (RSI7,SMA5,ROC5, OHL), Neurons: 50	68,18%	$5,53
NARX (RSI7,SMA5,ROC5, OHL), Neurons: 100	59,09%	$6,60
NARX (AD,RSI7,SMA5,EMA5,ROC5, OHL), Neurons: 10	77,27%	$14,88
NARX (AD,RSI7,SMA5,EMA5,ROC5, OHL), Neurons: 20	72,73%	$14,01
NARX (AD,RSI14,SMA10,EMA10,ROC10,OHL), Neurons: 10	86,36%	$18,36
NARX (AD,RSI14,SMA10,EMA10,ROC10,OHL), Neurons: 20	59,09%	$7,11
NARX (RSI7,RSI14,SMA5,SMA10,OHL), Neurons: 10	77,27%	$17,93
NARX (RSI7,RSI14,SMA5,SMA10,OHL), Neurons: 20	77,27%	$15,29

Conclusion

In the theoretical part of the thesis basic information about trading, different kinds of instruments, neural networks or trading charts, was provided. That was only to introduce the reader into the topic this thesis focuses on. The main part of the work is in the solution part where historical prices of Live Cattle commodity were analyzed and future prices predicted.

The main goal of the thesis was to design an universal solution of predicting the future prices of a commodity that would have success rate, or the probability of accurate prediction of the trend, of at least 50% - if that was not the case, flipping a coin would provide about the same accuracy for the investment decision. Fortunately the algorithm designed in MATLAB is much more accurate and can be used in serious trading situations.

There were two different models of the neural network used. The first one was nonlinear autoregressive (NAR) and the second one was nonlinear autoregressive with external input. Without any doubt, the latter one was much more successful in predicting the future prices reaching up to a success rate of 95,45% - in that particular situation, the developed algorithm was able to predict the trend (increase, decrease) of the price in 21 out of 22 instances. In other words, the trader in this case would now the price movement direction correctly for every out of 21 business days.

The beginning of testing of the developed solution was quite disappointing as the NAR network did not perform well at all. Success rate of around 55% is not reliable and no responsible trader would base their investment decision on that. But when suitable technical indicators were added to the NARX network, it started performing surprisingly well and there was not a single case of loss using the NARX network with external inputs of the technical indicators. The goal, which was set at the beginning of this thesis, is therefore considered as well achieved.

This solution could serve FNZ in case of any financial troubles, but as mentioned in the introduction, the goal was to design a universal solution that can be used by anybody.

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List of acronyms and abbreviations

Acronym / Abbreviation	Definition
OHL	Open, High, Low price
AD line	Accumulation/distribution line
RSI7	Relative Strength Index, period 7 days
RSI14	Relative Strength Index, period 14 days
OTC	Over-the-counter
SMA5	Simple Moving Average, period 5 days
SMA10	Simple Moving Average, period 10 days
EMA5	Exponential Moving Average, period 5 days
EMA10	Exponential Moving Average, period 10 days
ROC5	Price Rate Of Change, period 5 days
ROC10	Price Rate Of Change, period 10 days

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Attachment 1: NARX network – 10 neurons, external: AD, RSI7, SMA5, EMA5, ROC5, OHL (Source: designed by the author)

NARX (AD,RSI7,SMA5,EMA5,ROC5, OHL), Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	151,032	RISE	RISE	YES	-1,231	0,644
17.4.2015	149,902	146,853	148,111	FALL	FALL	YES	-1,258	3,050
20.4.2015	146,453	144,568	145,393	FALL	FALL	YES	-0,825	1,885
21.4.2015	144,531	145,823	146,903	RISE	RISE	YES	-1,081	1,291
22.4.2015	145,735	145,227	147,256	RISE	FALL	NO	-2,029	-0,508
23.4.2015	145,490	148,212	148,522	RISE	RISE	YES	-0,311	2,721
24.4.2015	148,431	150,064	149,247	RISE	RISE	YES	0,816	1,633
27.4.2015	148,118	148,816	148,475	FALL	FALL	YES	0,341	-0,698
28.4.2015	148,851	149,286	149,797	RISE	RISE	YES	-0,511	0,435
29.4.2015	149,673	149,594	149,849	RISE	RISE	YES	-0,254	-0,079
30.4.2015	149,718	148,608	149,759	RISE	FALL	NO	-1,150	-1,110
1.5.2015	148,459	148,455	148,358	FALL	FALL	YES	0,097	0,004
4.5.2015	148,701	149,770	151,135	RISE	RISE	YES	-1,365	1,069
5.5.2015	150,098	150,508	148,937	FALL	RISE	NO	1,571	-0,410
6.5.2015	150,410	149,720	149,749	FALL	FALL	YES	-0,029	0,690
7.5.2015	149,615	149,133	150,264	RISE	FALL	NO	-1,130	-0,482
8.5.2015	149,825	150,468	149,229	RISE	RISE	YES	1,239	0,643
11.5.2015	150,685	149,342	148,857	FALL	FALL	YES	0,484	1,344
12.5.2015	149,437	150,249	147,763	FALL	RISE	NO	2,486	-0,812
13.5.2015	150,108	151,253	151,548	RISE	RISE	YES	-0,295	1,145
14.5.2015	151,856	152,640	153,741	RISE	RISE	YES	-1,101	0,784
15.5.2015	152,952	151,308	150,206	FALL	FALL	YES	1,102	1,644
						77,27%		$14,88

Attachment 2: NARX network – 20 neurons, external: AD, RSI7, SMA5, EMA5, ROC5, OHL (Source: designed by the author)

NARX (AD,RSI7,SMA5,EMA5,ROC5, OHL), Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	150,950	RISE	RISE	YES	-1,149	0,644
17.4.2015	149,902	146,853	147,710	FALL	FALL	YES	-0,857	3,050
20.4.2015	146,453	144,568	145,756	FALL	FALL	YES	-1,188	1,885
21.4.2015	144,531	145,823	147,091	RISE	RISE	YES	-1,269	1,291
22.4.2015	145,735	145,227	145,054	FALL	FALL	YES	0,174	0,508
23.4.2015	145,490	148,212	147,933	RISE	RISE	YES	0,278	2,721
24.4.2015	148,431	150,064	150,357	RISE	RISE	YES	-0,293	1,633
27.4.2015	148,118	148,816	147,890	FALL	FALL	YES	0,926	-0,698
28.4.2015	148,851	149,286	148,184	FALL	RISE	NO	1,103	-0,435
29.4.2015	149,673	149,594	148,945	FALL	RISE	NO	0,649	0,079
30.4.2015	149,718	148,608	148,253	FALL	FALL	YES	0,355	1,110
1.5.2015	148,459	148,455	148,948	RISE	FALL	NO	-0,493	-0,004
4.5.2015	148,701	149,770	149,210	RISE	RISE	YES	0,560	1,069
5.5.2015	150,098	150,508	149,326	FALL	RISE	NO	1,182	-0,410
6.5.2015	150,410	149,720	148,717	FALL	FALL	YES	1,003	0,690
7.5.2015	149,615	149,133	149,066	FALL	FALL	YES	0,067	0,482
8.5.2015	149,825	150,468	149,518	RISE	RISE	YES	0,950	0,643
11.5.2015	150,685	149,342	153,211	RISE	FALL	NO	-3,870	-1,344
12.5.2015	149,437	150,249	150,129	RISE	RISE	YES	0,120	0,812
13.5.2015	150,108	151,253	151,575	RISE	RISE	YES	-0,322	1,145
14.5.2015	151,856	152,640	153,798	RISE	RISE	YES	-1,158	0,784
15.5.2015	152,952	151,308	152,802	RISE	FALL	NO	-1,494	-1,644
						72,73%		$14,01

Attachment 3: NARX network – 10 neurons, external: AD, RSI14, SMA10, EMA10, ROC10, OHL (Source: designed by the author)

NARX (AD,RSI14,SMA10,EMA10,ROC10,OHL), Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	151,232	RISE	RISE	YES	-1,431	0,644
17.4.2015	149,902	146,853	148,527	FALL	FALL	YES	-1,674	3,050
20.4.2015	146,453	144,568	144,781	FALL	FALL	YES	-0,214	1,885
21.4.2015	144,531	145,823	148,592	RISE	RISE	YES	-2,769	1,291
22.4.2015	145,735	145,227	144,060	FALL	FALL	YES	1,167	0,508
23.4.2015	145,490	148,212	149,379	RISE	RISE	YES	-1,167	2,721
24.4.2015	148,431	150,064	149,788	RISE	RISE	YES	0,276	1,633
27.4.2015	148,118	148,816	147,787	FALL	FALL	YES	1,029	-0,698
28.4.2015	148,851	149,286	148,466	FALL	RISE	NO	0,820	-0,435
29.4.2015	149,673	149,594	149,909	RISE	RISE	YES	-0,314	-0,079
30.4.2015	149,718	148,608	146,778	FALL	FALL	YES	1,830	1,110
1.5.2015	148,459	148,455	150,053	RISE	FALL	NO	-1,599	-0,004
4.5.2015	148,701	149,770	152,296	RISE	RISE	YES	-2,526	1,069
5.5.2015	150,098	150,508	151,744	RISE	RISE	YES	-1,236	0,410
6.5.2015	150,410	149,720	149,812	FALL	FALL	YES	-0,092	0,690
7.5.2015	149,615	149,133	149,666	FALL	FALL	YES	-0,533	0,482
8.5.2015	149,825	150,468	149,845	RISE	RISE	YES	0,623	0,643
11.5.2015	150,685	149,342	149,896	FALL	FALL	YES	-0,554	1,344
12.5.2015	149,437	150,249	150,121	RISE	RISE	YES	0,128	0,812
13.5.2015	150,108	151,253	149,667	FALL	RISE	NO	1,586	-1,145
14.5.2015	151,856	152,640	151,730	RISE	RISE	YES	0,910	0,784
15.5.2015	152,952	151,308	150,132	FALL	FALL	YES	1,176	1,644
						86,36%		$18,36

Attachment 4: NARX network – 20 neurons, external: AD, RSI14, SMA10, EMA10, ROC10, OHL (Source: designed by the author)

NARX (AD,RSI14,SMA10,EMA10,ROC10,OHL), Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,616	RISE	RISE	YES	0,185	0,644
17.4.2015	149,902	146,853	151,284	RISE	FALL	NO	-4,432	-3,050
20.4.2015	146,453	144,568	146,478	FALL	FALL	YES	-1,910	1,885
21.4.2015	144,531	145,823	146,481	RISE	RISE	YES	-0,658	1,291
22.4.2015	145,735	145,227	145,290	FALL	FALL	YES	-0,062	0,508
23.4.2015	145,490	148,212	148,961	RISE	RISE	YES	-0,750	2,721
24.4.2015	148,431	150,064	151,379	RISE	RISE	YES	-1,315	1,633
27.4.2015	148,118	148,816	145,677	FALL	FALL	YES	3,139	-0,698
28.4.2015	148,851	149,286	148,421	FALL	RISE	NO	0,865	-0,435
29.4.2015	149,673	149,594	148,190	FALL	RISE	NO	1,404	0,079
30.4.2015	149,718	148,608	147,750	FALL	FALL	YES	0,858	1,110
1.5.2015	148,459	148,455	148,742	RISE	FALL	NO	-0,287	-0,004
4.5.2015	148,701	149,770	147,651	FALL	RISE	NO	2,119	-1,069
5.5.2015	150,098	150,508	149,669	FALL	RISE	NO	0,839	-0,410
6.5.2015	150,410	149,720	151,646	RISE	FALL	NO	-1,927	-0,690
7.5.2015	149,615	149,133	153,722	RISE	FALL	NO	-4,589	-0,482
8.5.2015	149,825	150,468	150,717	RISE	RISE	YES	-0,248	0,643
11.5.2015	150,685	149,342	148,876	FALL	FALL	YES	0,466	1,344
12.5.2015	149,437	150,249	152,076	RISE	RISE	YES	-1,827	0,812
13.5.2015	150,108	151,253	147,683	FALL	RISE	NO	3,570	-1,145
14.5.2015	151,856	152,640	151,882	RISE	RISE	YES	0,757	0,784
15.5.2015	152,952	151,308	150,709	FALL	FALL	YES	0,599	1,644
						59,09%		$7,11

Attachment 5: NARX network – 10 neurons, external: RSI7, RSI14, SMA5, SMA10, OHL (Source: designed by the author)

NARX (RSI7,RSI14,SMA5,SMA10,OHL), Neurons: 10								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	149,300	RISE	RISE	YES	0,500	0,644
17.4.2015	149,902	146,853	145,186	FALL	FALL	YES	1,667	3,050
20.4.2015	146,453	144,568	144,510	FALL	FALL	YES	0,058	1,885
21.4.2015	144,531	145,823	146,042	RISE	RISE	YES	-0,220	1,291
22.4.2015	145,735	145,227	147,605	RISE	FALL	NO	-2,377	-0,508
23.4.2015	145,490	148,212	150,906	RISE	RISE	YES	-2,695	2,721
24.4.2015	148,431	150,064	148,961	RISE	RISE	YES	1,102	1,633
27.4.2015	148,118	148,816	151,181	RISE	FALL	NO	-2,365	0,698
28.4.2015	148,851	149,286	148,696	FALL	RISE	NO	0,590	-0,435
29.4.2015	149,673	149,594	150,514	RISE	RISE	YES	-0,920	-0,079
30.4.2015	149,718	148,608	148,257	FALL	FALL	YES	0,351	1,110
1.5.2015	148,459	148,455	147,942	FALL	FALL	YES	0,512	0,004
4.5.2015	148,701	149,770	146,696	FALL	RISE	NO	3,075	-1,069
5.5.2015	150,098	150,508	150,932	RISE	RISE	YES	-0,424	0,410
6.5.2015	150,410	149,720	149,129	FALL	FALL	YES	0,590	0,690
7.5.2015	149,615	149,133	149,845	RISE	FALL	NO	-0,712	-0,482
8.5.2015	149,825	150,468	149,161	RISE	RISE	YES	1,307	0,643
11.5.2015	150,685	149,342	149,056	FALL	FALL	YES	0,286	1,344
12.5.2015	149,437	150,249	151,055	RISE	RISE	YES	-0,806	0,812
13.5.2015	150,108	151,253	150,775	RISE	RISE	YES	0,478	1,145
14.5.2015	151,856	152,640	153,953	RISE	RISE	YES	-1,314	0,784
15.5.2015	152,952	151,308	150,232	FALL	FALL	YES	1,076	1,644
						77,27%		$17,93

Attachment 6: NARX network – 20 neurons, external: RSI7, RSI14, SMA5, SMA10, OHL (Source: designed by the author)

NARX (RSI7,RSI14,SMA5,SMA10,OHL), Neurons: 20								
Date	Open	Close real (Target)	Close predicted (Output)	Predicted trend	Real Trend	Prediction success	Error (Target - Output)	Open vs Close difference
15.4.2015	148,342	149,111						
16.4.2015	149,157	149,801	148,552	FALL	RISE	NO	1,249	-0,644
17.4.2015	149,902	146,853	146,735	FALL	FALL	YES	0,118	3,050
20.4.2015	146,453	144,568	140,704	FALL	FALL	YES	3,864	1,885
21.4.2015	144,531	145,823	145,344	RISE	RISE	YES	0,478	1,291
22.4.2015	145,735	145,227	149,226	RISE	FALL	NO	-3,999	-0,508
23.4.2015	145,490	148,212	149,107	RISE	RISE	YES	-0,895	2,721
24.4.2015	148,431	150,064	147,327	FALL	RISE	NO	2,736	-1,633
27.4.2015	148,118	148,816	146,637	FALL	FALL	YES	2,180	-0,698
28.4.2015	148,851	149,286	149,188	RISE	RISE	YES	0,099	0,435
29.4.2015	149,673	149,594	148,931	FALL	RISE	NO	0,664	0,079
30.4.2015	149,718	148,608	143,942	FALL	FALL	YES	4,666	1,110
1.5.2015	148,459	148,455	148,065	FALL	FALL	YES	0,389	0,004
4.5.2015	148,701	149,770	149,193	RISE	RISE	YES	0,577	1,069
5.5.2015	150,098	150,508	148,973	FALL	RISE	NO	1,535	-0,410
6.5.2015	150,410	149,720	149,230	FALL	FALL	YES	0,490	0,690
7.5.2015	149,615	149,133	147,902	FALL	FALL	YES	1,231	0,482
8.5.2015	149,825	150,468	150,147	RISE	RISE	YES	0,321	0,643
11.5.2015	150,685	149,342	147,381	FALL	FALL	YES	1,961	1,344
12.5.2015	149,437	150,249	152,681	RISE	RISE	YES	-2,432	0,812
13.5.2015	150,108	151,253	151,527	RISE	RISE	YES	-0,273	1,145
14.5.2015	151,856	152,640	151,563	RISE	RISE	YES	1,076	0,784
15.5.2015	152,952	151,308	150,521	FALL	FALL	YES	0,787	1,644
						77,27%		$15,29